Essays on the Determinants of Changing Employment and Wage Structures

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von
Dipl.-Vw. Charlotte Cornelia Senftleben-König, geb. Senftleben,

Präsident der Humboldt-Universität zu Berlin:
Prof. Dr. Jan-Hendrik Olbertz

Dekan der Wirtschaftswissenschaftlichen Fakultät:
Prof. Dr. Ulrich Kamecke

Gutachter:
1. Prof. Dr. Alexandra Spitz-Oener
2. Prof. Dr. Jochen Kluve

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To Philipp

Abstract

This thesis consists of four essays that contribute to the empirical literature on the determinants of recent changes in the employment and wage structure in Germany. The first essay analyzes recent employment growth at the lower tail of the wage distribution and its relation to technological progress. An econometric analysis suggests that technological progress has shifted the demand from routine intensive occupations towards low-paying service occupations that require non-routine manual tasks, which are difficult to be replaced by information technologies, thereby contributing to the polarization of the employment structure. The second essay explores the role of technological change in the evolution of spatial wage inequality. The results indicate technological change is one driver of wage inequality by increasing the compensation for non-routine cognitive tasks, and by decreasing the compensation for routine and non-routine manual tasks. The third essay exploits regional variation in the liberalization of shop-closing legislation in Germany to identify the causal impact of product market deregulation on employment outcomes in the retail sector. The results from the empirical analysis suggest that the deregulation had moderately negative effects on retail employment, leading to a loss of approximately 19,000 full-time equivalent jobs. The reason is that deregulation induced a change in the market structure by significantly decreasing the number of small retail stores which are relatively more personnel-intensive than larger formats. The fourth essay provides an empirical analysis of the impact of changes in public sector employment on employment in the private sector at the level of local labor markets. It shows that expansions in public employment can be associated with a sizeable crowding out effect on private sector employment. Moreover, the results indicate that employment losses are concentrated in the tradable sector.

Keywords:
Labor economics, technological change, tasks, occupational changes, local labor markets, product market regulation, natural experiments, public sector employment, local multipliers

Zusammenfassung

Diese Dissertation umfasst vier Essays, die einen Beitrag zur empirischen Literatur über die Determinanten der Veränderungen in der Beschäftigungs- und Lohnstruktur in Deutschland leisten. Im ersten Aufsatz wird der Zusammenhang zwischen technologischem Wandel und Wachstum von Beschäftigung am unteren Ende der Lohnverteilung untersucht. Eine ökonometrische Analyse zeigt, dass technologischer Wandel die Arbeitsnachfrage von routine-intensiven Berufen hin zu Berufen verschiebt, die niedrig entlohnte manuelle Tätigkeiten erfordern und sich nicht zur Substitution durch Informationstechnologien eignen. Damit trägt er zur Polarisierung der Beschäftigungsstrukturen bei. Der zweite Aufsatz untersucht die Rolle von technologischem Wandel in der Entstehung räumlicher Lohnungleichheiten. Es wird gezeigt, dass technologischer Wandel zu einem Zuwachs in der Entlohnung von nicht-routine kognitiven Tätigkeiten und zu einem Rückgang der Entlohnung für routine und nicht-routine manuelle Tätigkeiten führte und damit zur Vergrößerung der inter- und intra-regionalen Lohnungleichheit beitrug. Der dritte Aufsatz untersucht die Beschäftigungswirkung von Produktmarktderegulierung am Beispiel der Liberalisierung der Ladenschlussgesetze, wobei regionale Variation in der Gesetzgebung zur Identifikation des kausalen Effekts dient. Es wird gezeigt, dass die Beschäftigung im Einzelhandel durch die Deregulierung um etwa 19.000 vollzeitäquivalente Stellen zurückging. Dem zugrunde liegt ein signifikanter Rückgang an kleinen Unternehmen, die personalintensiver arbeiten als große Unternehmen. Im vierten Aufsatz werden die Auswirkungen von öffentlicher Beschäftigung auf die Beschäftigung im Privatsektor untersucht. Ergebnis ist, dass die Schaffung öffentlicher Beschäftigung erhebliche Verdrängungseffekte auf die Gesamtbeschäftigung im Privatsektor hat, wobei hauptsächlich der handelbare Sektor von Beschäftigungsverlusten betroffen ist.

Schlagwörter:
Arbeitsmarktökonomik, technologischer Wandel, Tätigkeiten, Berufswechsel, lokale Arbeitsmärkte, Produktmarktregulierung, natürliche Experimente, öffentliche Beschäftigung, lokale Multiplikatoren

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1 Introduction

The study of changing employment structures over time is of abiding interest for labor economists and policy makers alike. This dissertation provides empirical studies of different determinants of changes in employment and wage structures in Germany. These are (i) the role of technological progress (studied in chapters 2 and 3), (ii) the impact of product market deregulation (chapter 4), and (iii) the consequences of public sector employment growth (chapter 5).

One major trend, common to many industrialized countries, is the deterioration of labor market outcomes for low-educated workers. In Germany, for example, the qualification-specific unemployment rate of the low-skilled has risen from 5.1% in 1980 to 21.9% in 2009, beeing 19.4 percentage points higher than the unemployment rate of high-skilled employees. At the same time, real wages of low-skilled workers have declined since the beginning of the 1990's. One of the most popular hypotheses about the driving forces behind these changes emphasizes the skill-biased nature of technological change (Krueger, 1993; Machin and Reenen, 1998).

This view has recently been challenged by the task-based approach to technological change (Autor et al., 2003). The authors argue that technology can substitute for human labor in routine tasks, which are well-defined and follow explicit rules, whereas it cannot replace labor in non-routine tasks. Interestingly, Autor et al. (2003) show that routine tasks are not only performed by low-skilled workers. Instead, many clerical and production occupations located in the middle of the skill distribution are characterized by high routine task contents. What is more, non-routine tasks are not only performed by high-skilled employees (i.e. non-routine cognitive tasks), but rather many low-skilled employees work in occupations that are non-routine (manual) in nature, such as housekeeping and personal care. As a consequence, technological change leads to employment polarization, characterized by expanding employment shares of the highest and the least paid occupations at the expense of occupations located in the middle of the skill distribution.

The first two essays of this dissertation (chapter 2 and 3) build on concepts of the task-based approach in order to study this employment polarization in Germany and its relation to technological progress. In the context of this thesis, technological progress is defined as a pronounced exogenous decline in the price for information technology. Chapter 2 "The Polarization of Employment in German Local Labor Markets" addresses the question whether technological progress is related to growth of low-skilled occupations that require large inputs of non-routine tasks and are thus difficult to be substituted by information technologies. In order to establish empirical relationships, the analysis exploits variation across spatial units. Specifically, a local labor market measure is constructed that reflects how intensively routine tasks were used in local production *before* technological change kicked in. The results indicate that local labor markets that heavily used routine tasks witnessed a stronger adoption of computer technology, combined with a higher reduction in the usage of routine labor inputs. Further, initially routine labor intensive regions have experienced a stronger growth in personal service occupations, although this development is restricted to female employees. A complementary analysis of wages suggests that female employment gains in service occupations were accompanied by significant wage losses. Taken together, these opposite developments of employment and wages suggest that the supply of personal services rose faster than the demand for them. This stands in sharp contrast to findings of related studies for the United States, where employment polarization has been accompanied by wage polarization (Autor and Dorn, 2013). Hence, this highlights the importance of demand side factors in explaining differences in the evolution of employment and wages across industrialized countries.

Chapter 3 “Spatial Wage Inequality and Technological Change” is based on the findings of chapter 2 and explores the role of technological progress in the evolution of regional wage inequality. More specifically, it addresses the question whether technological progress exerts an impact on task compensation patterns, thereby eventually affecting wage inequality. The results of this analysis suggest that the rise in non-routine cognitive tasks was accompanied by an increase in their compensation, while the decline in routine tasks came along with decreases in their compensation. What is more, increases in non-routine manual tasks coincided with a decline in their pay. Given the fact that non-routine cognitive tasks are prevalent at the upper tail of the wage distribution, whereas routine and non-routine manual tasks are often times loacated at the lower parts of the distribution, the changes in the compensation structure of tasks point to an increase of overall wage inequality. Indeed, local labor markets which were initially specialized in routine intensive employment witnessed significant increases in local wage inequality as measured by the Gini-coefficient. The estimates suggest that a region at the 85th percentile of the routine share distribution increased its Gini-coefficient by 21% more than a region at the 15th percentile. This chapter contributes to the existing literature by directly relating technological change to developments in task-specific compensation patterns. Building upon the results of this analysis, evidence on the link between technological change and developments of intra- and inter-regional wage inequality is provided.

The analyses of the first two chapters are based on the Sample of Integrated Employment Biographies Regional File, augmented by information on tasks from the “Qualification and Career Survey”. This dataset is particularly well suited for our research as it includes detailed information on the activities individuals perform at the workplace.

The analyses in the last two chapters of this dissertation differ from the previous chapters as they are concerned with changing employment structures at the sectoral level. Existing literature has pointed towards the relevance of the regulatory environment of product markets for sectoral employment outcomes (see, among others, Krueger and Pischke (1997); Bertrand and Kramarz (2002)). From a theoretical point of view, there is no clear-cut prediction on how deregulation affects sectoral employment: One the one hand, deregulation increases productivity, so less employment is needed for a given level of output. On the other hand, productivity gains reduce prices and increase final demand, thus output and employment may increase. The analysis in Chapter 4 “Product Market Deregulation and Employment Outcomes: Evidence from the Germany Retail Sector” is an analysis of the labor market effects of product market deregulation in the retail sector resulting from a reform of shop closing legislation in 2006 and 2007. The study exploits regional variation in trading provisions across German federal states to uncover the employment effects. In a first step, the analysis assesses the aggregate employment effect of the policy reform. The results suggest that the deregulation modestly decreased employment in the German retail sector, leading to a loss of approximately 19,000 full-time equivalent jobs. In a second step, the study explores the changes in the employment structure that underlie this aggregate negative effect. It is shown that deregulation has caused a significant decline in the number of small establishments which operate more personnel-intensively than larger formats. Hence, the findings suggest that deregulation has enhanced the structural change of employment in the retail sector from smaller shops towards larger formats. The analysis in this chapter is based on the German Establishment History Panel, which covers employment information for 50% of all establishments with at least one employee subject to social security contributions.

The last chapter of this dissertation “Public Sector Employment and Local Multipliers” investigates the effects of public sector employment creation on the employment structure in the private sector at the level of local labor markets in Germany. In general, economic theory postulates two opposing effects of public employment creation on labor market outcomes in the private sector. On the one hand, aggregate demand is raised and therefore additional private sector employment is created. On the other hand, private employment may be redued due to upward pressure on wages. Moreover, by producing goods that are close substitutes to goods provided by the private sector, public sector employment creation harms employment in the private sector. Previous studies in this field predominantly use cross-country variation in public employment levels to establish a relationship between public and private sector employment growth (Boeri et al., 2000; Algan et al., 2002). Further, there are few studies that take into account possible problems arising from reverse causality or endogeneity. The analysis in this chapter seeks to close this gap by providing an empirical analysis at the level of German local labor markets and employing an instrumental variable strategy to isolate exogenous shifts in local public sector employment. In addition, this study contributes to the literature by analyzing the effect of public sector employment creation on wages in the private sector.

The results indicate that public sector employment programs have significant crowding out effects on employment in the private sector. The estimates suggest that each additional job in the public sector destroys .74 jobs in the local private sector. The analysis further indicates that public sector employment has an impact on the structure of employment in the private sector. By raising local private sector wages, employment in the tradable sector decreases as the competitiveness of these industries deteriorates. In nontradable industries, these negative effects are offset by an increase in local demand, so that employment in this sector remains relatively unchanged. The analysis in this chapter uses official data on overall and public sector employment from the Federal and Regional Statistical Offices, augmented by individual-level employment information from the Sample of Integrated Employment Biographies, aggregated at the district level.

All three subsequent chapters are supposed to be self-containing and can be read independently. Chapter 2 and 3 are based on joint work with Hanna Wielandt.

2 The Polarization of Employment in German Local Labor Markets

2.1 Introduction

In many industrialized countries, employment growth has been concentrated among low- and high-skilled employees, while the employment outcomes of workers in the middle of the skill distribution have deteriorated.[1] As illustrated in Figure 2.1, this pattern is also evident for Germany. The Figure plots the change in occupational employment shares for different subperiods between 1979 and 2006 ranked by occupational skill level, which is approximated by the respective median wage in 1979. It reveals that employment in high-skill occupations grew at the expense of less-skill occupations in all periods. In addition, particularly between 1990 and 2000, employment also grew at lower percentiles, resulting in the typical u-shaped pattern of employment polarization.

This study empirically analyzes the occupational shifts that drive the twisting of the employment distribution and their relation to technological progress. In order to directly link labor market outcomes to technological change, we use variation in technology exposure at the level of local labor markets. Our analysis builds on the seminal paper by Autor et al. (2003) that links job polarization to rapid productivity increases that came along with substantial declines in real prices of information and communication technologies. To understand the labor market impact of this development, work is conceptualized into a series of tasks, characterized as *routine* and *non-routine*, depending on their substitutability or complementarity with computer technology (see Acemoglu and Autor (2011) for a comprehensive overview of the task literature). Routine tasks are well-defined and follow explicit rules, which makes them particularly susceptible to substitution by computer technology. In contrast, computers complement *non-routine cognitive* tasks that involve high complexity and problem-solving, as they rely heavily on information as an input, resulting in productivity gains of employees performing these tasks. *Non-routine manual* tasks, which require environmental and interpersonal adaptability, are not directly influenced by computerization.

[1]For the US, Autor et al. (2006) show that medium-skilled employment has deteriorated relative to low- and high-skilled employment starting in the 1990's, corroborating the conjecture that technological change is rather task- than skill-biased. Goos and Manning (2007) find similar trends for Great Britain, showing that employment in occupations with the lowest and highest median wages in 1979 grew in subsequent decades, while employment in the middle of the distribution declined. Using data from the European Union Labour Force Survey, Goos et al. (2009b; 2014) present similar evidence for labor market polarization in 16 Western European countries.

Declining demand for routine tasks leads to employment polarization because tasks are not evenly distributed across the skill distribution. Figure 2.2 depicts the distribution of task usage in occupations across the skill distribution, which is approximated by the occupational median wage in 1979. It shows that non-routine cognitive tasks are prevalently performed in occupations located at the top of the skill distribution, while routine and non-routine manual tasks are mainly performed by less-skilled workers.

In a recent study, Autor and Dorn (2013) extend this conceptual framework to a two sector spatial equilibrium setting. In their model, technological progress displaces less-skilled workers performing routine tasks in the production of goods, which induces them to supply non-routine manual tasks to produce services instead. The positive labor supply effect initially depresses wages in less-skilled services. Yet, the authors show that employment polarization is accompanied by wage polarization if the increase in the supply of workers performing non-routine manual tasks is offset by an increase in the demand for these tasks, which occurs if goods produced by routine labor and services produced by non-routine manual labor are at least weakly complementary to each other. If, however, goods and services are not complementary, the demand for services does not rise sufficiently to increase the price for non-routine manual relative to routine tasks and wages do not polarize. Autor and Dorn (2013) test the hypotheses derived from the theoretical model for the United States at the level of commuting zones and find robust support for technology driven employment and wage polarization. These findings confirm existing evidence at the aggregate level presented, amongst others, by Autor et al. (2008) and Acemoglu and Autor (2011). They further show that the twisting of the lower tail of the employment and wage distribution is almost exclusively attributable to the growth of service occupations, an employment category which requires disproportionally high inputs of non-routine manual tasks.

To our knowledge, we are the first to test the implications of the model proposed by Autor and Dorn (2013) for the German labor market. We show that local labor markets differed substantially in the degree to which they employed routine task performing labor at the onset of technological change. Given this initial task specialization, regions were differently exposed to technological change. Previewing our key results, we show that regions with high initial routine employment shares adopted information technology faster, combined with a higher reduction in the use of routine labor inputs. We then present evidence that routine-intensive labor markets also experienced stronger employment growth in personal service occupations, although this development is restricted to female employees. Our analysis of wages suggests that female employment gains in service occupations were accompanied by significant wage losses. These opposite developments provide evidence that in Germany, the supply of personal services rose faster than the demand for them. This stands in contrast to findings for the United States, where employment polarization has been accompanied by wage polarization. Hence, our findings highlight the importance of demand side factors in explaining differences in the evolution of employment and wages across industrialized countries. We complement our analysis by exploring alternative adjustment patterns in

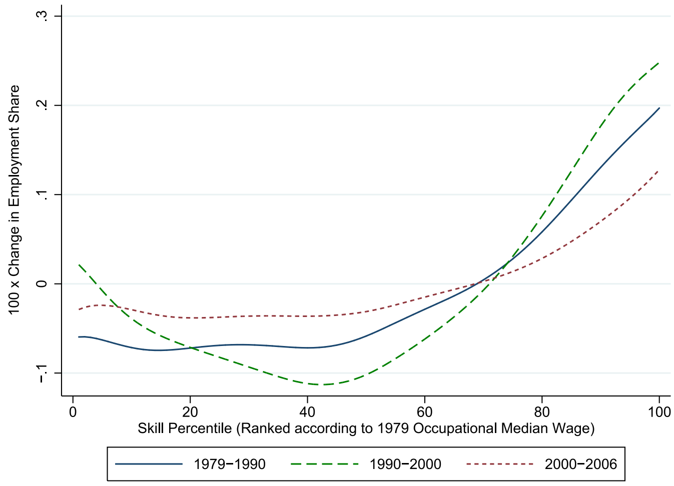


Figure 2.1: Smoothed Changes in Employment by Skill Percentile

Notes: Smoothed changes in employment by skill percentile in indicated periods. Occupations are ranked according to their 1979 median wage using the SIAB-R. Locally weighted smoothing regression with 100 observations and bandwidth 0.8.

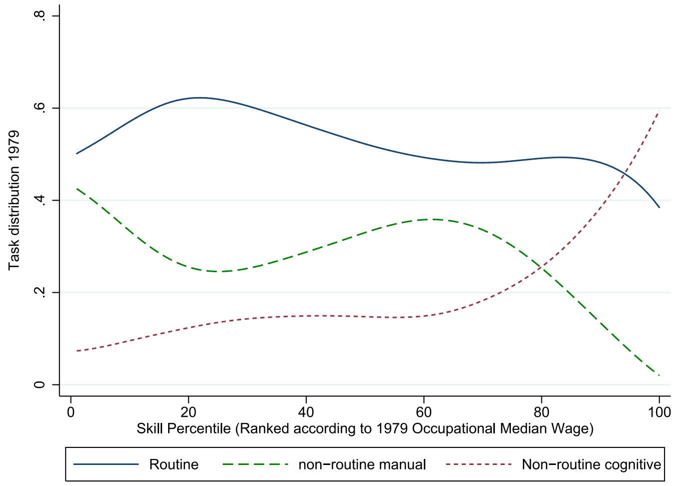


Figure 2.2: Task Inputs by Skill Percentile

Notes: Shares of workers performing routine, non-routine manual and non-routine cognitive tasks. Occupations are ranked according to their 1979 median wage using the SIAB-R. Task intensity is derived from BIBB/IAB wave 1979 and defined as in equation 2.3.

migration and unemployment, but find no robust evidence that labor markets have responded to technological shocks along these margins.

Our study advances the literature on employment polarization in Germany, which documents a polarizing pattern of employment (Spitz-Oener, 2006; Dustmann et al., 2009), but has so far focused on aggregate developments. By directly linking technological change to labor market outcomes at the regional level, we are able to explore the underlying mechanisms of polarization. Our results on regional wage patterns complement previous research for Germany that presents evidence for wage dispersion rather than compression at the lower tail of the wage distribution (Dustmann et al., 2009; Kohn, 2006; Antonczyk et al., 2010, 2009). Yet, as existing studies mainly focus on explanations such as deunionization and implicit minimum wages, we add to the understanding of recent wage developments by showing that technological change has reinforced the dispersion of the wage distribution.

The remainder of this chapter proceeds as follows. In section 2.2, we describe the empirical approach, the data set and the variables used in our analysis. Section 2.3 presents summary evidence on trends in regional task intensities and information technology. We then investigate the relationship between the regional routine share and the growth of routine and non-routine employment, focusing on trends in personal service employment. Furthermore, we analyze whether employment developments are accompanied by wage trends in the same direction and consider alternative adjustment mechanisms such as unemployment and migration. Section 2.4 concludes.

2.2 Data and Methods

2.2.1 Empirical Approach and Estimation Strategy

Our empirical approach is closely linked to the strategy in Autor and Dorn (2013), which exploits the variation in industry specialization patterns across regions. The starting point of the analysis is the observation that at the onset of technological progress, regions employed different shares of routine, non-routine manual and non-routine cognitive task inputs depending on the task requirements for the production of particular goods and services. These differences in regional task structures create variation in the degree to which regions are exposed to technological change. Hence, we are able to directly link employment and wage outcomes to a measure of technology exposure and to test the predictions derived from the spatial model presented by Autor and Dorn (2013). In particular, we explore whether regions characterized by a strong initial exposure to technological change

1. adopt information technology to a larger extent and exhibit a differential decline in routine employment,
2. experience larger growth in non-routine employment, particular in personal service occupations, resulting in employment polarization,
3. experience wage polarization,
4. witness a differential increase in unemployment and outward migration.

In order to analyze the relationship between the regional task structure in 1979 and subsequent employment and wage changes, we set up an empirical model of the following form:

$$\Delta Y_r = \alpha + \beta_1 RSH_r + \mathbf{X_r'}\beta_2 + \gamma_s + e_r. \tag{2.1}$$

Depending on which of the aforementioned hypotheses is tested, the dependent variable Y_r represents the change in one of the following measures in region r between the years 1979 and 2006: (1) share of employees working with a computer, (2) share of employees performing routine, non-routine manual or non-routine cognitive tasks, (3) share of personal service employment in overall employment, (4) employment shares and wages in different major occupational groups, and (5) unemployment rate and net migration share.[2] The main parameter of interest, β_1, is the coefficient on the measure of regional technology exposure in 1979, RSH_r, as measured by the share of routine employment in a specific region *before* technological progress kicked in. As computerization only started to spur during the 1980's, the routine employment share in 1979 should be largely unaffected by computerization (Autor et al., 1998; Bresnahan, 1999).[3]

All regressions include state dummies, γ_s, that control for mean differences in employment and wages across states. The model includes additional covariates, summarized by the vector X_r, which control for the regional human capital and demographic composition as well as for local economic conditions in 1979.

2.2.2 Data and Construction of Variables

Data Sources: Labor Market Outcomes

All information concerning local employment and wages is obtained from the Sample of Integrated Labor Market Biographies Regional File (SIAB-R), a two percent random sample drawn from the full population of the Integrated Employment Biographies, provided by the Institute of Employment Research by the Federal Employment Agency. This highly reliable administrative data comprises marginal, part-time and regular employees as well as job searchers and benefit recipients (for details, see Dorner et al. (2011)). The dataset provides detailed information on daily wages for employees subject to social security contributions (wages of civil servants and self-employed workers are not included), as well as information on occupation, industry affiliation, workplace location and demographic information on age, gender, nationality and educational attainment.

We restrict the sample to prime-aged workers (males and females) between 20 and 60

[2] Autor and Dorn (2013) employ stacked first differences over three time periods to estimate the relationship between regional routine intensity and the growth of non-college service employment. If we follow this approach we obtain very similar results in terms of effect size and statistical significance as shown in Table 2.5, section 2.3.2.

[3] Nordhaus (2007) estimates that after a period of very modest price decreases in the 1960's and 1970's, the cost of computation sharply declined thereafter.

years of age working in West Germany and exclude public sector and agricultural workers. Employment is expressed in full-time equivalents, following the weighting procedure proposed by Dauth (2013). For the analysis of wages we use information on real gross daily wages of employees. As the data lacks information on hours worked, wages of part-time employees are measured less accurately and we are forced to restrict our analysis to full-time workers. Whenever aggregate or average outcomes are constructed, each employment spell is weighted by the number of days worked. The Data Appendix provides more details on the sample selection and the basic processing of the SIAB-R.

For the analysis it is crucial to consider functionally delineated labor market regions (Eckey et al., 2006; Eckey and Klemmer, 1991). To reflect local labor markets more appropriately, we take commuter flows into account and aggregate the 326 administrative districts in West Germany to 204 labor market regions following Koller and Schwengler (2000).

In order to construct regional control variables, we include information from the Establishment History Panel (BHP), a 50 percent sample of all establishments throughout Germany with at least one employee liable to social security, stratified by establishment size (Gruhl et al., 2012). The additional covariates are expressed as fractions of overall full-time employment and chosen to control for the qualification and demographic structure as well as for general economic conditions at the local level. Descriptive statistics for the regional covariates in 1979 and 2006 are summarized in Table 2.1.

Measuring Task Supplies

The information on task requirements of employees is derived from the BIBB/IAB Qualification and Career Survey (QCS) in 1979 which covers approximately 30,000 individuals (Rohrbach-Schmidt, 2009). The dataset is particularly well suited for our research as it includes detailed information on the activities individuals perform at the workplace. For each individual i, these activities are pooled into three task categories: (1) non-routine cognitive, (2) routine and (3) non-routine manual tasks. In the assignment of tasks we follow Spitz-Oener (2006) and construct individual task measures TM_i^j for task j in the base year 1979 according to the definition of Antonczyk et al. (2009):

$$TM_i^j(1979) = \frac{\text{\# of activities in category } j \text{ performed by } i \text{ in 1979}}{\text{total \# of activities performed by } i \text{ over all categories in 1979}} \times 100, \quad (2.2)$$

where $j = C$ (non-routine cognitive), R (routine) and M (non-routine manual). In order to match the task information to the SIAB-R, the individual task measures are aggregated at the occupational level, where the task input of individual i in occupation k in 1979 is weighted by its respective weekly working hours $L_{ik}(1979)$:

$$TI_k^j(1979) = \left(\sum_i \left[L_{ik}(1979) \times TM_{ik}^j(1979)\right]\right) \left(\sum_i L_{ik}(1979)\right)^{-1}. \quad (2.3)$$

To obtain task measures at the regional level, the occupational task information from the QCS is matched to the SIAB-R, exploiting the fact that both datasets employ a time-consistent definition of occupational titles according to the three-digit 1988 occupational classification provided by the Federal Employment Agency. As the focus of our analysis lies on occupational shifts induced by technological change, we abstract from changes in the task structure within occupations over time and construct task supplies $T_r^j(t)$ for each region r and time t as:

$$T_r^j(t) = \left(\sum_k \left[L_{kr}(t) \times TI_k^j(1979) \right] \right) \left(\sum_k L_{kr}(t) \right)^{-1}, \tag{2.4}$$

where $L_{kr}(t)$ is employment in occupation k in labor market r at time t. Thus, changes in $T_r^j(t)$ represent only the between-occupational dimension of task shifts. Summary statistics of the three task measures in 1979 and 2006 are provided in the upper Panel of Table 2.1. The average share of routine and non-routine manual tasks declined slightly between 1979 and 2006 while non-routine cognitive tasks became more prevalent. The relatively modest changes in regional task structures confirm existing evidence showing that most of the task adjustments occur within occupations (Spitz-Oener, 2006).

Similar to the task shares, we construct a measure of regional computer usage with information derived from the QCS. Regional computer prevalence is measured as the share of employees using one of the following devices: (1) personal computers, (2) terminals or (3) electronic data-processing machines in region r in 1979 and 2006. Table 2.1 confirms that the use of personal computers at the workplace has increased tremendously from 5% in 1979 to 75% in 2006.

Measuring Technology Exposure

Our main explanatory variable is a measure that reflects the regional exposure to technological progress. To generate this, we follow the approach of Autor and Dorn (2013): we use the occupational routine task index in 1979, $TI_k^R(1979)$ to identify the occupations in the upper third of the routine task distribution. We calculate for each labor market r a routine employment share measure RSH_r for the year 1979, equal to:

$$RSH_r = \left(\sum_k L_{kr} \times \mathbb{I}\left[TI_k^R > TI_k^{R,P66} \right] \right) \left(\sum_k L_{kr} \right)^{-1}, \tag{2.5}$$

where L_{kr} is employment in occupation k in labor market r in 1979, and $\mathbb{I}[\cdot]$ is an indicator function, which takes the value of one if the occupation is routine-intensive. The average regional routine share in 1979 is .423. A region at the 85th percentile of the routine share distribution has a 7.4 percentage points higher routine intensity than a region at the 15th percentile ($RSH^{P15} = .387$, $RSH^{P85} = .461$). To get an impression of the spatial variation in technology exposure, Appendix Figure 6.1 maps the geographic distribution of the regional routine intensity in 1979 across Germany. Regions with a strong exposure to technological change constitute a mixture of industrial strongholds, such as Wuppertal and Wolfsburg, as well as human capital intensive regions, such as Düsseldorf and Cologne.[4] Hence, a high exposure to technological change is not only related to the existence of a large manufacturing sector in a region, but also stems from the prevalence of white-collar clerical and administrative support occupations. Regions with a low routine share tend to be specialized in the tourism and hospitality industry or are often located near the Alps or the sea, for example Husum or Bad Reichenhall.

Table 2.1: Descriptive Statistics for German Local Labor Markets

Variable	1979	2006
Average task shares and PC use		
Non-routine cognitive (T^C)	.168	.193
	(.015)	(.017)
Routine (T^R)	.537	.534
	(.019)	(.020)
Non-routine manual (T^M)	.295	.273
	(.025)	(.027)
Personal Computer Use (*PC*)	.051	.753
	(.011)	(.034)
Main explanatory variable		
Routine share	.423	–
	(.038)	–
Covariates		
Fraction full-time employed/total pop.	.250	.217
	(.067)	(.059)
Fraction female employees/full-time empl.	.330	.323
	(.045)	(.038)
Fraction foreign employees/full-time empl.	.081	.108
	(.048)	(.052)
Fraction high to low- and medium-skilled full-time empl.	.030	.095
	(.016)	(.051)
Fraction manufacturing empl./full-time empl.	.439	.354
	(.125)	(.118)
Average region population	297,494	313,296
	(376,437)	(359,030)
Population density	301	317
(number of inhabitants per square kilometer)	(418)	(400)

Notes: $N = 204$ labor market regions. Standard deviations in parentheses. All employment variables are based upon employment subject to social security contributions for a given region. Fractions are computed with respect to total full-time employment.

[4] In 1979, the share of manufacturing employment in overall employment in Wuppertal and Wolfsburg amounts to 54% and 83%, respectively, which is far above the average. For both, Düsseldorf and Cologne, the share of high-skilled employees is more than two standard deviations larger than the average.

2.3 Results

2.3.1 Task Specialization, Adoption of IT and the Displacement of Routine Tasks

The task-based framework predicts that information technology substitutes for routine tasks performing labor, thereby inducing a reallocation from routine to non-routine manual task intensive labor. Hence, we expect labor markets that were particularly exposed to technological progress to differentially adopt computer capital, alongside pronounced changes in the regional task structure. In the following, we will test these predictions, starting with computer adoption. To this end, we regress the change in regional computer penetration between 1979 and 2006 on the technology exposure measure, state dummies and a measure of population density to capture differences in urban concentration across regions, as described by equation 2.6:

$$\Delta PC_r = \alpha + \beta_1 RSH_r + \beta_2 dens_r + \gamma_s + e_r. \tag{2.6}$$

The results, displayed in the first column of Table 2.2, indicate that computer adoption is indeed positively correlated with a region's initial exposure to technological progress. To interpret the estimated coefficient quantitatively, we compare the predicted changes in computer adoption of a region at the 15th percentile of the technology exposure distribution with a region at the 85th percentile. The point estimate of .151 implies a differential increase of 1.1 percentage points. Relative to an average increase in computer adoption of almost 70 percentage points between 1979 and 2006, the economic significance of the coefficient is rather small.[5]

In a next step, we explore whether computer adaption was accompanied by displacement of routine employment. To do so, we estimate a variant of equation 2.6, where the dependent variable is the change in the regional routine employment share between 1979 and 2006. The negative coefficient in column 2 of Table 2.2 confirms this hypothesis, implying that a region at the 85th percentile of the technology exposure measure experienced a differential decrease in routine employment by 1.6 percentage points relative to a region at the 15th percentile. To put this number into perspective, it is compared to a relatively modest average decline in the (between-occupational) routine share of around .4 percentage points. Thus, the estimated coefficient is of substantial economic significance, reinforcing the general downward trend in routine-intensive employment.

Columns 3 and 4 present complementary estimates for the change in the non-routine manual and non-routine cognitive task shares. The results show that relative declines in routine-intensive employment are primarily offset by significant increases in the supply of non-routine manual tasks (column 3). In contrast, changes in non-routine cognitive task

[5] As we only consider the use of personal computers, our measure of computer prevalence is limited in its ability to reflect technological progress.

inputs are positive but remain insignificant.[6] This is not surprising given that the performance of non-routine cognitive tasks usually requires a relatively high skill level or some educational attainment that might not be met by workers who formerly engaged in routine tasks.

Table 2.2: Changes in the Shares of Regional Routine and Non-Routine Employment, 1979-2006

Dependent variable: Δ 1979-2006	ΔPC	ΔT^R	ΔT^M	ΔT^C
	(1)	(2)	(3)	(4)
Panel A: All				
Routine Share 1979	.151***	-.217***	.180***	.037
	(.042)	(.036)	(.034)	(.029)
R^2	.366	.234	.229	.102
Panel B: Men				
Routine Share 1979	.203***	-.202***	.154***	.048
	(.054)	(.045)	(.041)	(.037)
R^2	.333	.169	.165	.130
Panel C: Women				
Routine Share 1979	.064*	-.173***	.180***	-.006
	(.036)	(.051)	(.049)	(.027)
R^2	.295	.190	.167	.067

Notes: $N = 204$ labor market regions. All models include dummies for the federal state in which the region is located, a measure of population density (number of inhabitants per square kilometer) as well as a constant. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

To explore whether task adjustment patterns are uniform across genders, Panel B and C display the results separately for male and female workers. Technology exposure predicts a more pronounced increase in computer usage combined with a larger decline in the performance of routine tasks for male workers compared to female counterparts. Further, female employees have exclusively reallocated their task supply towards non-routine manual tasks, while males also experienced slight increases in non-routine cognitive tasks, although the coefficient on the routine share is imprecisely estimated.

As the emphasis of this study lies on occupational shifts, the changes in the dependent variable solely reflect between-occupational changes and abstract from changes in the task structure within occupations. Yet, it bears notice that the same conclusions can be drawn when considering both within- and between-occupational task changes (Senftleben-König and Wielandt, 2014a).

[6]The sum of the three task shares adds up to one by construction. Therefore, as a region's routine employment share declines, the other shares automatically increase. However, it is noteworthy that losses in routine employment are not distributed uniformly to both the non-routine manual and the non-routine cognitive employment share.

2.3.2 The Growth of Personal Service Sector Employment

Overall Trends in Major Occupational Groups

So far, we have shown preliminary evidence of a significant technology-related shift away from routine towards non-routine employment at the level of regional labor markets. Bearing in mind the polarizing pattern of employment depicted in Figure 2.1, the question arises whether this growth in non-routine manual tasks indeed drives the twisting of the lower tail of the wage distribution.

To investigate this question in greater detail, Table 2.3 displays task intensities in 1979 for five broad occupational groups, classified according to Blossfeld (1985). Notably, two employment categories are dominated by non-routine manual task inputs: Personal service occupations, which involve assisting and caring for others, such as hairdressers, cleaners, table waiters and security guards, as well as construction occupations, such as painters and carpenters.[7] Both occupations exhibit high shares of employees without formal education, but differ significantly from each other with respect to their location on the occupational wage distribution. That is, employees performing construction occupations earn on average 15% percent more than workers in service occupations, who have the lowest average wage across the occupational groups. More importantly, the share of workers employed in service occupations grew by roughly 18% between 1979 and 2006, while construction occupations witnessed a sharp decline by 4.7 percentage points over the same period. Table 2.3 additionally depicts aggregate employment patterns and the occupational task structure in 1979 separately by gender. Although the share of employees working in service occupations grew for men and women, the numbers reveal stronger increases for women by approximately 1.5 percentage points. Furthermore, the share of low-educated workers is larger for the female subsample which is also reflected in lower average wages across all occupations. While the occupational routine task intensities are similar for both genders, women's work has on average lower non-routine cognitive task contents and higher non-routine manual tasks contents. Interestingly, service occupations are distinct in their gender-specific task structure in the sense that women mainly perform non-routine manual tasks, while men equally provide routine and non-routine manual tasks.

As personal service occupations exhibit low wages, high levels of non-routine manual task inputs and have experienced high levels of employment growth, this particular occupational group deserves special attention when investigating the phenomenon of employment polarization. The relevance of employment developments in personal service occupations for employment polarization becomes evident in Figure 2.3. Here we illustrate a counterfactual situation of employment growth along the skill distribution between 1990 and 2000, with service employment held constant at its 1990 level. Apparently, employment polarization

[7] It bears emphasis that in the context of our analysis, service *occupations* are to be distinguished from the service *sector*: While service occupations mainly comprise less-skilled personal services, the service sector represents a broad category of industries that can also be highly knowledge-intensive.

Table 2.3: Employment, Wages and the Task Structure by Broad Occupation Categories 1979

	Task structure			%low-	Empl.	Log	Δ 1979-2006	
	T^C	T^R	T^M	skilled	share	Wage	Empl.	Wages
All								
Professionals	.438	.389	.173	.024	.114	4.460	.020	.063
Clerical/Sale	.126	.844	.030	.089	.238	4.099	.050	.150
Production	.117	.554	.328	.190	.354	4.146	-.055	.032
Construction	.129	.391	.480	.183	.118	4.213	-.047	.016
Service	.138	.353	.513	.179	.177	4.062	.032	-.032
Males								
Professionals	.476	.406	.118	.038	.128	4.581	.004	.090
Clerical/Sale	.152	.823	.025	.074	.119	4.389	.042	.099
Production	.115	.541	.344	.269	.405	4.256	-.006	-.011
Construction	.131	.390	.479	.194	.178	4.219	-.066	.017
Service	.137	.426	.437	.297	.169	4.218	.026	-.087
Females								
Professionals	.349	.349	.303	.066	.088	4.131	.048	.112
Clerical/Sale	.115	.853	.032	.153	.460	3.940	.030	.150
Production	.124	.589	.287	.706	.256	3.819	-.118	.042
Construction	.080	.429	.491	.683	.004	3.827	-.001	.080
Service	.136	.246	.623	.462	.191	3.754	.041	.085

Notes: SIAB Regional File. Sample includes persons aged 20 to 60 living in West Germany. Military and agricultural employment is excluded. Labor supply is measured as the number of days worked in a given year. Part-time work is included and weighted by average working hours according to Dauth (2013).

would have occurred in the counterfactual scenario as well, while the positive growth of employment at the lower tail of the wage distribution is exclusively attributable to the growth of personal service occupations. In contrast, developments at the upper tail of the distribution are not related to services.

Baseline Estimates

Having shown that the evolution of personal service occupations plays a crucial role when investigating the phenomenon of employment polarization, we will now analyze whether this growth is related to technological change, as shown for the US by Autor and Dorn (2013). In order to directly link employment trends to technological change, we will conduct this investigation within the framework of a regression analysis at the level of local labor markets. As we are mainly interested in employment dynamics at the lower tail of the wage distribution, we restrict the analysis to low- and medium-skilled employees.[8]

We begin by estimating a model described by equation 2.1, where the dependent variable is the change in the share of service employment in overall employment between 1979 and

[8]While the model proposed by Autor and Dorn (2013) focuses on employment changes of low-skilled labor exclusively, we consider developments among both low- and medium-skilled workers. This is due to the special nature of the German vocational system, in which there is a vocational degree for the vast majority of existing occupations. If we restricted our analysis to low-skilled workers only, we would concentrate on a rather small subset of employees working in service occupations, which is not the purpose of our investigation.

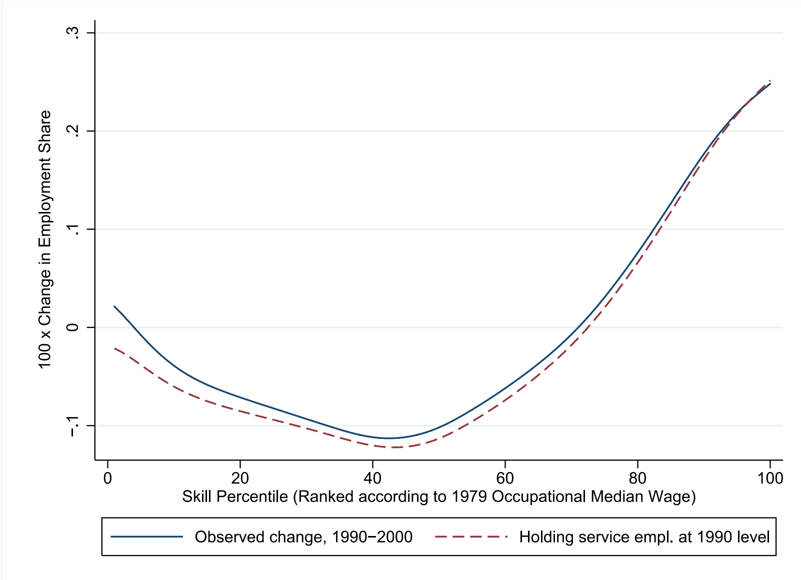


Figure 2.3: Observed and Counterfactual Changes in Employment by Skill Percentile, 1990-2000

Notes: Smoothed changes in employment by skill percentile between 1990 and 2000. Occupations are ranked according to their 1979 median wage using the SIAB Regional File. To construct the counterfactual we keep service employment at its 1990 level. Locally weighted smoothing regression with 100 observations and bandwidth 0.8.

2006. The positive and significant estimate, displayed in column 1 of Table 2.4, suggests that regions which were prone to computerization witnessed a differential growth in service employment. The estimated coefficient of .107 implies that a region at the 85th percentile of the routine share distribution is predicted to increase its share of personal service employment by .8 percentage points more than a region at the 15th percentile over the observed period. Given an average increase of 2.2 percentage points, the degree to which a region is exposed to technological change is of substantial economic significance for later employment developments.

As other local labor market conditions might affect the growth of local service sector employment, the model is augmented step-by-step by additional control variables as displayed in the remaining columns of Table 2.4. Column 2 includes a measure of population density to control for differences in the degree of urbanization across regions, with the estimate on the routine share being virtually unaltered. Columns 3 to 5 add variables that are expected to influence the demand for personal services. Column 3 includes the fraction of the regional population subject to social security contributions, which serves as a proxy for the regional employment rate. A higher share of working population should raise the demand for personal services such as restaurant meals or housekeeping as household production is substituted by market-based production of services. This substitution effect is supported by the positive albeit insignificant coefficient reported in column 3. Along the lines of this argument, the regression is further augmented with the share of female employees which

Table 2.4: Estimated Impact of Technology Exposure on Service Sector Employment

Dep. variable: Δ SVC employment 1979-2006	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				A. Total employment				
Routine Share 1979	.107**	.104**	.097*	.084*	.100**	.092*	.120**	.104*
	(.049)	(.049)	(.050)	(.051)	(.050)	(.050)	(.052)	(.055)
Share employed/pop.			.037	.060	.017	.024		.060
			(.064)	(.059)	(.069)	(.066)		(.064)
Share female/empl.				.065				.034
				(.053)				(.059)
High/low skilled empl.					.120			.023
					(.115)			(.125)
Share foreign empl./empl						.038		.033
						(.043)		(.047)
Share manuf. empl./empl							-.027	-.022
							(.017)	(.019)
Population density	no	yes	yes	yes	yes	yes	yes	yes
R^2	.114	.116	.118	.127	.123	.121	.130	.135
				B. Male employment				
Routine Share 1979	.034	.024	.010	-.013	.016	.004	.057	.033
	(.060)	(.060)	(.061)	(.063)	(.061)	(.061)	(.065)	(.069)
R^2	.134	.150	.155	.170	.170	.156	.183	.191
				C. Female employment				
Routine Share 1979	.247***	.256***	.267***	.265***	.263***	.259***	.249***	.241***
	(.067)	(.065)	(.066)	(.070)	(.066)	(.069)	(.069)	(.075)
R^2	.124	.133	.135	.135	.138	.136	.137	.142

Notes: $N = 204$ labor market regions. All regressions include dummies for the federal state in which the region is located, regional covariates as indicated as well as a constant. Covariates in all Panels are identical and enter with the expected sign. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

we suspect to increase service sector employment (Manning, 2004; Mazzolari and Ragusa, 2013). The positive coefficient on the fraction of female employment in column 4 supports this conjecture. Column 5 adds the ratio of high- to low-skilled workers as a measure to reflect differences in the educational structure across regions. Its positive sign suggests that a higher relative supply of high-skilled workers is related to larger growth of service employment. The inclusion of each of the potential demand shifters decreases the size of the coefficient of interest, rendering it less statistically significant in some cases. Column 6 adds an indicator that potentially influences the supply of services by including the share of the working population that has foreign nationality (Cortes, 2008). Indeed, this variable is positively related to the growth of service employment, but the point estimate is not statistically different from zero. Again, the inclusion leads to a decline of the coefficient on the regional routine intensity. As local labor demand conditions might be relevant for regional employment patterns, column 7 includes the share of manufacturing employment, which dampens the growth in service occupations. Once we include the full set of covariates in the model (column 8), the estimate on the regional routine share is similar in size compared to the coefficient reported in the baseline specification in the first column but is less precisely estimated and significant only at the 10% level.

So far, we have implicitly assumed that the relation between technological change and the growth of service sector employment is uniform across individuals. Given the steeper increase in service employment for female compared to male workers and higher levels of non-routine manual task inputs (see Table 2.3), this assumption might not be justified. Furthermore, Black and Spitz-Oener (2010) show that the polarization pressure has been more pronounced for female employees as women have been more exposed to technological change owing to a larger share of days worked in routine-intensive occupations. We therefore re-estimate the previous model separately for male and female employees and present the findings in Panel B and C of Table 2.4. Indeed, the results confirm the existence of gender-specific trends in the evolution of service employment. For male workers, there is effectively no correlation between the initial regional routine share and subsequent growth in personal service employment. As opposed to this, the point estimate for females is economically large and statistically significant irrespective of the inclusion of additional covariates. The predicted increase in service employment for the female sample in the region at the 85th percentile of the technology exposure distribution is 1.8 percentage points larger than in the 15th percentile region, a change that is more than twice as large as in the pooled sample.

Robustness Checks

So far, we have found evidence that regions which were particularly exposed to technological change experienced differential increases in service sector employment, although this adjustment is limited to female workers. In this section, we investigate the robustness of this main result to several specification choices and depict results in Table 2.5. For ease of comparison, the baseline estimate for the effect of technological change on service employment is reproduced in Panel 1.

We start by analyzing whether the results of our analysis hinge on the particular construction of our main explanatory variable, the regional routine share. To this end, we re-construct the technology exposure measure using the top 25 or 50 percent most routine-intensive occupations instead of the top tercile. In line with the baseline results, the estimates on the alternative routine share measures in Panel 2 are similar in magnitude to the baseline, although they are more precisely estimated. Consistent with the baseline results, the gender-specific estimates indicate that this positive effect is mainly driven by female service employment growth.

One concern about the simple OLS results is that they neglect the spatial dependency across single labor markets. To address this potential source of bias in the estimates, we re-estimate spatial error models with contiguity and inverse distance weighting. As the results in Panel 3 suggest, both weighting methods yield very similar point estimates compared to previous results. Moreover, there is only minor evidence of significant spatial autocorrelation as suggested by the Wald test statistic and the associated p-value.[9]

[9] While the contiguity matrix only consists of zeros and ones, the inverse-distance weighting matrix assigns weights that are inversely related to the distance between regions. Distance-based weight matrices are in general better suited to account for spatial dependency among regions than contiguity-based matrices as they

So far, the dependent variable in our analysis is the single difference in employment shares based on the year 1979. This approach focuses on the long-run component of differences in the regional task structures, thus circumventing the potential endogeneity problem related to the use of subsequent routine shares. Yet, as depicted in Panel 4, the results remain similar if we follow the empirical strategy by Autor and Dorn (2013) and employ stacked first differences over three time periods to estimate the relationship between technological change and subsequent growth in service employment.

Table 2.5: Robustness Checks, 1979 - 2006

Coefficient on RSH	All (1)	Males (2)	Females (3)
Panel 1: Baseline	.104*	.026	.254***
	(.058)	(.072)	(.078)
Panel 2: Alternative RSH measure			
50% most routine	.126**	.031	.281***
	(.055)	(.066)	(.082)
25% most routine	.164***	.118*	.220***
	(.051)	(.063)	(.083)
Panel 3: Spatial error models			
Inverse distance weighting	.101*	.022	.253***
	(.054)	(.068)	(.075)
Contiguity weighting	.100*	.026	.247***
	(.053)	(.062)	(.075)
Panel 4: Stacked first differences	.052*	.000	.148***
($N = 612$)	(.029)	(.034)	(.054)
Panel 5: Exclude border regions	.087	.024	.197**
($N = 171$)	(.062)	(.078)	(.087)
Panel 6: Contemporaneous changes	.094*	.041	.208***
	(.053)	(.067)	(.072)

Notes: $N = 204$ labor market regions (unless stated otherwise). Each cell reports the coefficient on the routine share for one separate regression. All models include a constant, dummies for the federal state in which the region is located, a measure of population density as well as the covariates listed in Table 2.4. Regressions in Panel 4 additionally include time dummies. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

While our study focuses on West German labor markets, the time period includes German reunification in 1990. For regions in close proximity to the former border, we may be concerned that our results are driven by exogenous increases in the labor supply due to migration following the fall of the wall. To rule out that this development drives our overall result, we exclude labor markets along the border. The results in Panel 5 are consistent with the results from the baseline specification. We further tested the generality of our results by experimenting with different subsamples depending on the size and the region type of the

describe the regional integration more accurately. As the coefficient estimates in our baseline analysis do not differ from the results obtained from the spatial weighting we are not concerned by the relatively low p-value when using the inverse distance weighting.

specific labor market. We obtain similar results considering urban or rural regions separately or estimating models for large (population>200 T in 1979) and small (population<=200 T in 1979) regions. Further, the conclusions of our analysis remain unaltered by the selection of different start and end dates.[10]

Finally, we repeat the OLS estimation using contemporaneous changes of the regional covariates instead of their 1979 levels. The resulting coefficients presented in Panel 6 are comparable in magnitude to the prior specifications. Nevertheless, it should be clear that some of these contemporaneous changes in the workforce composition are a result of technological change themselves (Autor and Dorn, 2013).

2.3.3 Employment and Wage Changes in Major Occupational Groups

The preceding analysis has shown that regional technology exposure is highly predictive of declining routine and rising non-routine employment, equally pronounced for men an women. It has also established a positive relationship between technological change and employment reallocation towards service occupations, although this development is restricted to female employees. To investigate further reallocation patterns, we now broaden the focus of our analysis beyond service employment and analyze employment changes in all other major occupational groups. The results are depicted in Table 2.6. In addition to service occupations, construction occupations and professional jobs are characterized by a high level of non-routine task contents. Theoretically, the share of these occupations in overall employment should increase - similar to what is observed in service occupations. In contrast, occupations with high routine task requirements, i.e. clerical and production occupations, should decline. In columns 1 to 3 of Panel A, we analyze the relationship between technological change and employment growth in non-routine intensive occupations. While employment gains in service occupations are realized by women only (column 1), column 2 highlights a differential reallocation of male employment into construction occupations. The coefficient of .197 is statistically highly significant and implies that a 7.4 percentage point higher routine share in 1979, equal to the gap between the 85th and the 15th percentile labor market, predicts a 1.5 percentage points higher increase in the employment share of construction occupations between 1979 and 2006. The estimates for professional occupations (e.g. scientist, professionals, teachers) are very small in magnitude and statistically insignificant for both males and females. This is not surprising, given that this group of occupations primarily employs workers with tertiary education which are excluded from our sample.

Columns 4 and 5 of Panel A present the results for two occupation groups with a high level of routine employment in 1979: clerical and sales occupations (e.g. bookkeeper, accountants, sales personnel) and blue-collar production occupations. The results verify that employment losses in routine-intensive occupations are more pronounced in routine-intensive regions, although the coefficients for clerical occupations are imprecisely estimated.

[10]Results are available from the authors upon request.

Table 2.6: Technology Exposure and Change in Occupational Employment, 1979 - 2006

		Service occ.	Construction occ.	Professionals/ Education	Clerical/ Sales	Production occ.
Panel A: Employment changes		(1)	(2)	(3)	(4)	(5)
I: All	Routine Share 1979	.104*	.197***	.012	-.059	-.254***
		(.055)	(.056)	(.048)	(.072)	(.096)
II: Males	Routine Share 1979	.033	.268***	-.033	-.059	-.208*
		(.069)	(.087)	(.063)	(.068)	(.109)
III: Females	Routine Share 1979	.241***	-.005	.085	-.022	-.298**
		(.075)	(.022)	(.057)	(.107)	(.121)
Panel B: Wage changes						
I: All	Routine Share 1979	-.010	.257***	.020	-.088*	.045
		(.039)	(.050)	(.045)	(.044)	(.042)
	N	140,485	80,907	80,106	160,944	253,620
II: Males	Routine Share 1979	.053	.247***	.076	.089	.048
		(.042)	(.050)	(.053)	(.057)	(.042)
	N	92,414	79,642	55,270	60,857	198,913
III: Females	Routine Share 1979	-.161**	.121	-.148*	-.184***	.063
		(.071)	(.888)	(.084)	(.057)	(.065)
	N	48,071	1,265	24,836	100,357	54,707

Notes: Panel A: $N = 204$ labor market regions. All models include a constant, dummies for the federal state in which the region is located, a measure of population density as well as the covariates listed in Table 2.4. Robust standard errors in parentheses.
Panel B: Regression models include an intercept, region-occupation group fixed effects, time trends for occupation groups and states, two dummies for education levels, a quartic in potential experience, dummies for foreign-born, and interactions of all individual level controls with the time dummy. Pooled sex models also include a female dummy and its interaction with the time dummy. Observations are weighted by each worker's number of days worked in the respective year.
Robust standard errors are clustered on the level of regions. * Significant at 10%, ** at 5%, *** at 1%.

To allow for further heterogeneity of the employment effects, we additionally split the overall sample into subsamples bifurcated by age (age 20-39 vs. age 40-60), education (low- and medium-skilled) and working-time arrangement (full-time vs. part-time) and present the results in Appendix Table 6.1. Employment patterns are very similar across the subsamples with some notable exceptions. The decline in routine-intensive occupations alongside a more pronounced reallocation towards service and construction occupations is more pronounced for older workers. For younger workers, the patterns are similar yet the coefficients are substantially smaller in size, resulting in estimates that are statistically insignificant (columns 1 and 2).[11] We also observe that employment of low- and medium-skilled workers evolves similarly. Notably, declines in production occupations are mainly realized by low-skilled employees, while medium-skilled workers experience employment

[11] This is in line with evidence presented by Autor and Dorn (2009), showing that the decline in routine-intensive jobs for older workers is almost entirely absorbed by employment gains in non-routine manual occupations.

losses in clerical and sales occupations. This is in line with descriptive evidence in Table 2.3, which shows that clerical and sales occupations have on average higher education levels compared to production occupations. Finally, the results separated by working-type indicate that full-time employment declines in both routine-intensive occupation groups and is offset by employment growth in construction occupations and to a somewhat smaller extent in services. Part-time employment on the other hand decreases mainly in production occupations and relocates solely towards services. However, the coefficients for part-time workers are less precisely estimated due to smaller sample sizes.

The spatial model by Autor and Dorn (2013) predicts that together with employment polarization, routine-intensive labor markets should experience a more pronounced earnings growth at both tails of the wage distribution. To analyze the relation between technological progress and wage changes, we pool wage data for the years 1979 and 2006 to regress log daily wages of individual i, in region r, state s, occupation k and time t on the main predictive variable RSH_r, separately for each of the five occupational groups:

$$\ln w_{irkts} = \alpha + \beta_1 \left(RSH_r \times \mathbb{I}\left[t = 2006\right] \right) + \mathbf{X_i'}\beta_2 + \phi_{rk} + \gamma_{ts} + e_{irkt}. \tag{2.7}$$

In this setting, the technology exposure variable is interacted with a dummy for the year 2006, thus reflecting the relationship between regional routine intensity in 1979 and subsequent wage growth. The regression is augmented with individual-level covariates (gender, education, nationality, a quartic in potential experience), their interactions with time dummies as well as region-occupation and time-state fixed effects. Because the main explanatory variable, RSH_r does not vary within regions, standard errors are clustered at the level of local labor markets (Moulton, 1986). The wage estimates are summarized in Panel B of Table 2.6. Most importantly, the pronounced increase in female service employment coincides with significant wage losses in this employment category. The coefficient of -.161 translates into a 1.2 log points larger decline in wages in a region at the 85th percentile of the distribution compared to the 15th percentile. These countervailing developments of employment and wages provide no evidence for increasing demand for personal services which contradicts findings for the United States. In contrast, employment gains in construction occupations realized by male workers are accompanied by significantly stronger wage growth in routine-intensive regions. A 7.4 point higher routine share in 1979 translates into larger wage growth by 1.8 log points.

Surprisingly, employment declines in routine-intensive occupations coincide with wage gains for male workers, although the estimates are rather small in size and imprecisely estimated. A potential explanation for this opposite movement of employment and wages are the pronounced within-occupational task shifts from routine to non-routine cognitive tasks (Senftleben-König and Wielandt, 2014a). Hence, the remaining workers may be a selective group with higher average skill and wage levels. For production occupations, a strong exporting sector in Germany offers a further explanation for stable wages (Dauth et al., 2014).

Altogether, our analysis provides robust evidence for a technology-related reallocation of labor supply from routine to non-routine manual tasks, a finding that is consistent with results obtained for the US by Autor and Dorn (2013). Although this development has been observed for males and females, we find some gender-specific adjustment patters when considering occupational shifts, which are dissimilar to the United States. In particular, our analysis shows that female employees cluster in service occupations, while male employees experience increases in construction occupations. Further, in contrast to findings for the US, employment growth in service occupations was accompanied by significant wage *losses* in this occupational group. One interpretation of this pattern is that the rising supply of service occupations was not met by sufficient demand increases in Germany, which might be depressed by higher payroll taxes, eventually resulting in more home- than market-based production (Freeman et al., 2005; Burda et al., 2007). This argument is in line with several other studies which document that many European countries seem to be missing personal services such as retail trade or hotel and restaurant employment (Piketty, 1997).

2.3.4 Alternative Adjustment Mechanisms

In this section, we complement our analysis of employment and wage changes and consider the impact of technological progress on other labor market outcomes. First, we explore whether technological change induced a reallocation of employees towards regions that are less affected by computerization. If labor flows are perfectly mobile across regions, workers should adjust to regional technology shocks by relocating between regions. Then, the impact of technological change would unfold through regional migration patterns instead of occupational shifts. To test for technology-induced population shifts, we regress the change in regional net migration shares of low- and medium-skilled employees between 1979 and 2006 on the routine share measure.[12] The model is estimated for the overall sample as well as separately by gender. The negative coefficients in the first two columns of Panel A in Table 2.7 suggest that regions that were prone to technological change experienced higher outward-migration. The negative coefficient of -.023 suggests a .17 percentage points larger outward migration in a region at the 85th percentile compared to a region at the 15th percentile of the routine share distribution. The coefficients for male workers (columns 3 and 4) are considerably larger than their female counterparts, indicating that adjustments along the margin of migration are more pronounced for males. However, the coefficients for both subsamples are imprecisely estimated.

One further margin of adjustment to technological change is selection into unemployment. We test for this possibility by exploring the relationship between technology exposure and

[12] We use the information from the SIAB-R to compute regional net migration shares for the years 1979 and 2006. In this context, migration is defined as a job change when the new job is in a different labor market than the previous one. As our definition builds upon job changes, and not simply changes of the place of residence, it fits well with the purpose of our analysis. Further details are discussed in the Data Appendix 6.1.1.

subsequent changes in the regional unemployment rate between 1981 and 2004.[13] The positive coefficients for the overall sample in Table B of Table 2.7 imply a differential increase in the unemployment rate in regions that were initially routine-intensive. Yet, with the inclusion of additional covariates (column 2), the magnitude of the point estimate declines by about half of its size and turns insignificant.[14] The separate results for male and female employees reveal no gender-specific differences in unemployment effects. Both coefficients are similar in magnitude and insignificant at conventional levels when the control variables are included.

Table 2.7: Estimated Impact of Technology Exposure on Net Migration and Regional Unemployment

	I. All		II. Males		III. Females	
	(1)	(2)	(3)	(4)	(5)	(6)
	A: Δ Net migration share 1979-2006					
Routine Share 1979	-.018	-.023	-.022	-.035	-.005	.001
	(.026)	(.025)	(.037)	(.038)	(.028)	(0.030)
R^2	.063	.121	.050	.097	.039	.049
	B: Δ Unemployment rate 1981-2004					
Routine Share 1979	.095**	.053	.090*	.060	.111**	.052
	(.042)	(.040)	(.050)	(.051)	(.044)	(.043)
R^2	.343	.391	.342	.392	.216	.276
Regional covariates	no	yes	no	yes	no	yes

Notes: $N = 204$ labor market regions. All regressions include a constant, dummies for the federal state in which the region is located, a measure of population density (number of inhabitants per square kilometer), and regional covariates listed in Table 2.4 as indicated. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

These findings, in combination with the results on occupational changes, suggest that the adjustment to technological change mainly occurred via the margin of employment, while there have been little or no technology-related shifts in migration patterns or unemployment. These findings are in line with existing literature on regional adjustments to labor market shocks, which shows that responses in regional mobility are relatively slow and incomplete, particularly among less-educated workers (Glaeser and Gyourko, 2005; Notowidigdo, 2011; Dauth et al., 2014). Furthermore, it has been shown that internal migration in Europe is much lower than in the US (Decressin and Fatàs, 1995; Nahuis and Parikh, 2002) and that adjustment processes to shocks occur mainly via lower participation rates.

[13] The unemployment rate is computed using the benefit recipient history included in the SIAB-R. Due to data limitations we are restricted to the shorter time period. See the Data Appendix 6.1.1 for details on the construction of the unemployment rate and robustness checks.

[14] Employment changes for the shorter time period from 1981 to 2004 are similar in magnitude and significance to our previous results for the longer time span between 1979 and 2006.

2.4 Conclusion

In recent decades, the employment structures of many industrialized countries have undergone substantial changes. This analysis examines the relation between technological progress and employment and wage polarization in Germany at the level of local labor markets. To do so, we exploit variation in the degree to which regions are exposed to technological change, as determined by local task structures.

Our results suggest that regions that were initially specialized in routine tasks adopted information technology faster and witnessed a larger displacement of routine employment. At the same time, these regions experienced a differential growth of occupations in which non-routine manual tasks are prevalent. We show that among these occupations, particularly the growth of the personal service sector contributed to the twisting of the lower tail of the employment distribution. Yet, our results suggest that the growth of service employment is gender-specific and exclusively attributable to employment growth of female workers. Men, instead, relocate towards construction occupations. While the employment results are generally consistent with findings for the US, our wage analysis has shown that supply increases in service occupations were accompanied by significant wage losses. Hence, our results highlight the importance of demand side factors when exploring the impact of technological change on the wage structure. We also investigated the possibility of interregional mobility and selection into unemployment as a response to technological change, but find no robust support for adjustments along these margins.

3 Spatial Wage Inequality and Technological Change

3.1 Introduction

The increase in wage inequality in many industrialized countries during the last decades has attracted considerable attention from economists, policy makers and the general public alike. A consensus view in the literature is that rising inequality is linked to differential demand shifts for high- and low-skilled workers.[1] Existing studies on the determinants of these shifts have mainly focused on explaining developments at the aggregate level. However, there are substantial differences in the evolution of wages across spatial units. To illustrate this fact, Figure 3.1 depicts the evolution of the mean and standard deviation of the composition-adjusted Gini-coefficient for wages in the 204 West German labor market regions. Between 1979 and 2006, the Gini-index rose by almost a quarter from .19 to .24. At the same time, the standard deviation nearly doubled, indicating that this average rise occurs to varying degrees in different regions. These spatial disparities are sizable, for example, the difference between the region with the lowest and the highest Gini-coefficient amounted to .16 in 2006, while it was only .08 in 1979.[2] Hence, the presence of rising regional dispersion suggests that demand and supply shifts for skilled and unskilled workers occur differentially across spatial units.

This chapter explores the spatial dimension of rising wage inequality in Germany between 1979 and 2006 and its determinants. We focus on the role of technological change which has proven a successful explanation for recent wage developments at the aggregate level. Our analysis builds upon a recent paper by Autor and Dorn (2013), who use the task-based approach to technological change to explain employment and wage dynamics. They argue that technological progress is non-neutral with respect to different job tasks that employees perform at the workplace (Autor et al., 2003).[3] Technological progress reduces the cost of automating codifiable, *routine* job tasks, which can be performed either by computer capital or low-skilled labor. This induces substitution from routine labor to computer capital and leads displaced workers to supply *non-routine manual* tasks instead. These do not

[1] Katz and Autor (1999) and Acemoglu and Autor (2011) offer an exhaustive overview of the facts.

[2] The same observation holds for alternative wage inequality measures, such as the Theil-index and the P85/P15 wage ratio.

[3] Acemoglu and Autor (2011) define a task as a unit of work activity, that produces goods and services. Workers allocate their skills to different tasks, depending on their comparative advantage in supplying them.

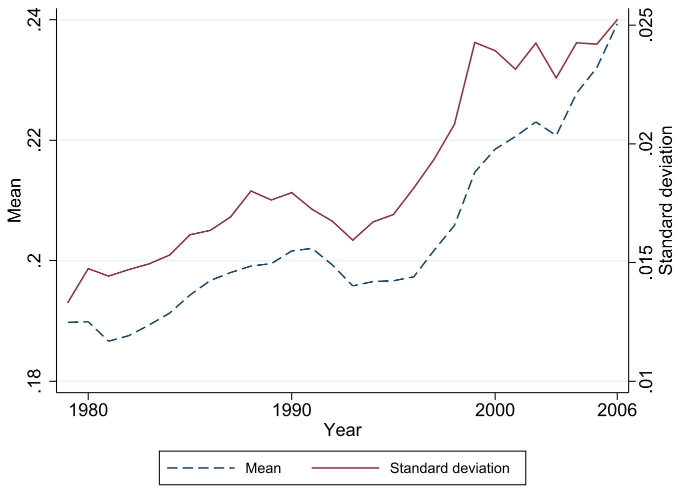


Figure 3.1: Evolution of Wage Inequality Over Time

Notes: N=204 labor market regions. In order to abstract from changes in the workforce composition we hold constant relative employment shares of demographic groups as defined by gender, education, nationality and potential experience. Gini-coefficients are calculated using the average labor supply share for each subgroup over 1979 to 2006 as fix weights.

require a high skill level but situational adaptability and personal interaction, and are thus unsuitable for substitution by technology. Simultaneously, technological progress increases the productivity of workers who perform problem-solving, *non-routine cognitive* tasks which are complemented by technology as they rely on information as an input. Technological change drives down the wages paid to routine tasks, and increases the compensation for non-routine cognitive tasks. The impact of technology on the wages paid for non-routine manual tasks is ambiguous, depending on whether the demand for these tasks rises enough to offset adverse wage effects stemming from additional supply.

This paper studies the implications of the task-based approach for regional wage inequality at the level of local labor markets. To do so, we exploit variation in the regional endowment of routine task performing labor, resulting from regional differences in industry structures. This paper makes two contributions to the existing literature. To our knowledge, we are the first to directly relate technological change to developments in task-specific compensation patterns. Building upon the results of this analysis, we then provide novel evidence on the link between technological change and developments of intra- and inter-regional wage inequality. Previewing our key results, regions with high technology exposure experienced a greater relocation from routine to non-routine employment. The rise in non-routine cognitive tasks was accompanied by an increase in their compensation, while the decline in routine tasks came along with decreases in their compensation. Further, increases in non-routine manual tasks coincided with a decline in their pay, suggesting that the demand for these tasks did not rise enough to compensate for the increase in supply.

Given the fact that non-routine cognitive tasks are prevalent at the upper tail of the wage distribution, while routine and non-routine manual tasks are most commonplace at the lower parts of the distribution, changes in the compensation structure of tasks should manifest in an increase of overall wage inequality. We present evidence that local labor markets that were initially specialized in routine intensive employment witnessed significant increases in local wage inequality as measured by the Gini-coefficient. Our estimates suggest that between 1979 and 2006, a region at the 85th percentile of the routine share distribution increased its Gini-coefficient by 21% more than a region at the 15th percentile.

We then address the question whether the spatial differences of technology exposure are an important determinant for the development of *inter-regional* inequalities. To this end, we compare wage developments, when hypothetically only one determinant of wage inequality is allowed to vary across regions, while all other factors remain constant. This dispersion analysis suggests that technology exposure is a relevant source of spatial disparities.

Our study combines the literature on the labor market effects of technology with work in urban economics on spatial dispersion of wages and skill premia. The former has conclusively documented the importance of technological progress in explaining changes in the aggregate wage and employment structure. Autor et al. (2006, 2008) show that both employment and wage growth has been u-shaped across the skill distribution in the Unites States. Similar employment patterns have been also detected in other industrialized countries (Spitz-Oener, 2006; Goos and Manning, 2007; Goos et al., 2009a; Michaels et al., 2014; Senftleben-König and Wielandt, 2014b). Yet, in contrast to the US, these countries have witnessed increases in wage inequality throughout the entire wage distribution (Gernandt and Pfeiffer, 2007; Antonczyk et al., 2010). In addition, existing studies for the German labor market did not establish a relationship between technological change and rising wage inequality. Instead, they emphasize the role of composition effects and labor market institutions (Dustmann et al., 2009; Antonczyk et al., 2009).

With respect to the latter, a number of studies have documented spatial persistence of wage differentials (Combes et al., 2008; Moretti, 2011; Combes et al., 2012), where research has primarily focused on the impact of agglomeration and urban wage premia (see Duranton and Puga (2004) and Rosenthal and Strange (2004) for an overview of the existing literature). Other explanations for regional wage differences are related to the impact of international trade (Hanson, 1997; Autor et al., 2013), and, more broadly, to the role of market access and infrastructure (Redding and Venables, 2004; Breinlich et al., 2014). Yet, evidence on the connection between wage inequality and technology at the regional level is sparse. One notable exception is a recent paper by Lindley and Machin (2014), who investigate spatial variation in the college wage premium across US states and report that relative demand increases for high-skilled labor are larger in states with higher increases in R&D spending. Further, a study by Autor and Dorn (2013), which is most closely related to our analysis, explores the role of technology for occupational employment and wage changes at the commuting zone level. They find that regions that were particularly prone to computerization experienced differential increases in non-routine occupations which coincided with wage gains in these occupations, leading to job and wage polarization.

The remainder of the chapter proceeds as follows: Section 3.2 shortly presents the theoretical model developed by Autor and Dorn (2013) (henceforth AD), a model of unbalanced productivity growth upon which our empirical analysis is based, and its key implications. Further, we describe the empirical approach used to test the model predictions and their consequences for the evolution of spatial labor market inequality. Section 3.3 introduces the datasets employed and describes how we construct our main explanatory variable, a measure to capture the impact of recent technological progress, as well as measures of regional task supply and compensation. In Section 3.4, we assess the relationship between technology exposure and regional developments in task supplies and task compensation patterns. Based upon these results, we explore the role of technology for the evolution of overall regional wage inequality in section 3.5. Section 3.6 concludes.

3.2 Theoretical Model and Estimation Strategy

3.2.1 Theoretical Model and Implications

Our analysis is based on a model of unbalanced productivity growth by AD. In their model, technological change takes the form of a decline in prices for computer capital which replaces routine-task labor. The model describes an economy where goods and services are produced using non-routine manual (L_m), routine (L_r) and non-routine cognitive (L_c) tasks, and computer capital (K) as inputs. Tasks are either supplied by high-skilled workers (H), who solely perform non-routine cognitive tasks, or low-skilled workers (L), who supply routine and non-routine manual tasks (L_r, L_m). Computer capital can be used to substitute for routine tasks. The production of output (Y_g) combines non-routine cognitive and routine labor as well as computer capital using the following production function:

$$Y_g = L_c^{1-\beta} \left[(\alpha_r L_r)^{\mu} + (\alpha_k K)^{\mu}\right]^{\beta/\mu} \tag{3.1}$$

with $\beta, \mu \in (0,1)$ and α_r>0 and α_k>0 reflecting efficiency parameters. Services (Y_s) are produced by means of non-routine manual labor only using the following linear production function:

$$Y_s = \alpha_m L_m \tag{3.2}$$

Households supply labor and consume goods and services. Their utility for consuming goods and services is given by a standard CES utility function.

$$u = (c_s^{\rho} + c_g^{\rho})^{1/\rho} \tag{3.3}$$

where $\sigma = 1/(1-\rho)$ measures the elasticity of substitution between goods and services. AD consider the case where the price of computer capital (p_k) goes to zero, as this is their definition of technological progress. They then solve for the asymptotic allocation of low-skill labor to services, which is uniquely determined as follows:[4]

$$\lim_{p_k \to 0} L_m^* = \begin{cases} 1 & \text{if } \frac{1}{\sigma} > \frac{\beta-\mu}{\beta} \\ \overline{L}_m \in (0,1) & \text{if } \frac{1}{\sigma} = \frac{\beta-\mu}{\beta} \\ 0 & \text{if } \frac{1}{\sigma} < \frac{\beta-\mu}{\beta}. \end{cases} \tag{3.4}$$

The allocation crucially depends upon the relative magnitudes of the two elasticities, scaled by the share of the routine task input in goods production (β). That is, if the production elasticity exceeds the consumption elasticity, technological change raises the relative demand for low-skill labor in service employment. Yet, if the reverse is true, low-skilled labor concentrates in the goods sector performing routine tasks.

The dynamics of the relative compensation paid to non-routine cognitive versus routine tasks ($\frac{w_c}{wr}$) and non-routine manual versus routine tasks ($\frac{w_m}{wr}$) mirror the dynamics of labor flows between goods and services. If the production elasticity exceeds the consumption elasticity, the compensation for non-routine manual tasks rises relative to the wage paid to routine tasks. If instead, the consumption elasticity is larger, demand for non-routine manual tasks does not rise sufficiently to increase compensation paid to these tasks.

$$\lim_{p_k \to 0} \frac{w_m}{w_r} = \begin{cases} \infty & \text{if } \frac{1}{\sigma} > \frac{\beta-\mu}{\beta} \\ -log(1-L_m*) & \text{if } \frac{1}{\sigma} = \frac{\beta-\mu}{\beta} \\ 0 & \text{if } \frac{1}{\sigma} < \frac{\beta-\mu}{\beta}, \end{cases} \tag{3.5}$$

In addition, the ratio between the compensation paid for non-routine cognitive to routine tasks always goes to infinity as computer prices fall to zero.

$$\lim_{p_k \to 0} \frac{w_c}{w_r} = \infty. \tag{3.6}$$

AD extend the model further to a spatial equilibrium setting with a large number of regions. The key feature is that technology has differential effects on local labor markets depending on the amount of routine task inputs employed in regional goods production. The results from this spatial model closely resemble the closed economy model.

This theoretical framework provides a number of predictions for the evolution of task requirements and task compensation patterns and thus for regional wage inequality. Firstly, the model predicts a general downward trend in routine task inputs, as these are subject to substitution by computer capital, where regions that were particularly exposed to technological change should experience greater declines in routine task requirements. Secondly,

[4] For the explicit derivation, the interested reader is referred to Autor and Dorn (2013).

the model predicts that decreases in routine tasks should come along with declines in the wages paid for these tasks. Because technological change increases the productivity of employees performing non-routine cognitive tasks, wages paid to these tasks should rise. The consequences for the non-routine manual task compensation is ambiguous as these depend on consumer preferences. More specifically, if consumers do not admit close substitutes for services (provided by non-routine manual tasks), technological change raises aggregate demand for non-routine manual tasks and hence their compensation. If, however, consumer preferences are different, the model predicts that the compensation for non-routine manual tasks declines. Thus, the model is consistent with wage polarization, as recently documented in the United States for example by Autor et al. (2008) as well as a monotonous increase of wage inequality throughout the skill distribution, a development that has been observed in Germany during the last decades (Dustmann et al., 2009). In that case, the model predictions are similar to the traditional skill-biased technological change hypothesis (Acemoglu and Autor, 2011).

3.2.2 Empirical Approach

In order to empirically test the relationships identified by the theoretical model in AD, we proceed in three steps. First, we assess the relationship between technology exposure and changes in task supplies across regions. Second, we explore the effects of computerization on the compensation of tasks. Third, we quantify the role of technology for the evolution of overall regional wage inequality. To do so, we estimate empirical models of the following form

$$\Delta Y_r = \alpha + \beta_1 RSH_r + \mathbf{X}'_r \beta_2 + \gamma_s + e_r. \tag{3.7}$$

The dependent variable ΔY_r represents the first difference of the variable of interest in region r between the base year 1979 and some subsequent year t. Depending on the hypothesis tested, ΔY_r represents (1) the regional supply of routine, non-routine manual and non-routine cognitive tasks, (2) the region specific compensation of routine, non-routine manual and non-routine cognitive tasks, and (3) the regional Gini-coefficient to reflect wage inequality within a region.[5]

The parameter of interest, β_1, is the coefficient on the main explanatory variable, RSH_r. This measure is defined as the share of routine intensive employment in region r in 1979 as reflects the degree to which a particular region is exposed to technological change. It should be largely unaffected by technological progress as computerization kicked in during

[5] Autor and Dorn (2013) employ stacked first differences over three time periods to estimate the relationship between regional routine intensity and subsequent employment changes. In contrast, we restrict our analysis to the single difference based on the routine shares and regional covariates in 1979 as the explanatory variables to focus on the long-run component of differences in regional task structures and thus circumvent the endogeneity problem related to the use of subsequent routine shares. If we follow the approach of AD, we obtain very similar results in terms of effect size and statistical significance.

the 1980's, as documented, for example, by Nordhaus (2007). All regressions include state dummies, γ_s, that control for mean differences in employment and wages across states. In addition, all regressions are weighted by the regional population size.

To control for potentially confounding factors, the model includes additional covariates, summarized by the vector X_r, reflecting differences in urbanity between regions, the local human capital and demographic composition as well as local economic conditions in 1979.

3.3 Data, Construction of Variables and Descriptive Evidence

3.3.1 Data Sources: Employment and Wages

All information concerning local employment and wages is obtained from the Sample of Integrated Labor Market Biographies Regional File (SIAB-R), a two percent random sample drawn from the full population of the Integrated Employment Biographies, provided by the Institute of Employment Research at the Federal Employment Agency. This highly reliable administrative dataset comprises marginal, part-time and regular employees as well as job searchers and benefit recipients covering the years 1975 to 2008 (for details, see Dorner et al. (2011)). It provides detailed information on daily wages for employees subject to social security contributions (wages of civil servants and self-employed workers are not included), as well as information on occupation, industry affiliation, workplace location and demographic information on age, gender, nationality and educational attainment. For our analysis, we restrict the sample to full-time workers (males and females) between 20 and 60 years of age working in West Germany. Whenever aggregate or average outcomes are constructed, each employment spell is weighted by the number of days worked.[6]

For the analysis it is crucial to consider functionally delineated labor market regions. In particular, to reflect local labor markets more appropriately, we take commuter flows into account (Eckey et al., 2006; Eckey and Klemmer, 1991). Following Koller and Schwengler (2000), we aggregate the 324 administrative districts in West Germany (excluding Berlin) to 204 labor market regions. In 1979, these labor market regions have an average population of around 300,000 individuals, although this varies from 55,000 to 2,5 million.

We use the wage information in the SIAB-R to compute the Gini-index, an inequality measure commonly used in the literature (e.g. by Kopczuk et al. (2010)). The index ranges from 0 (total equality) to 1 (total inequality) and is computed for every region and year. Alternatively, we conduct robustness checks by considering the Theil-index and the ratio of wages at the 85th percentile relative to the 15th percentile of the wage distribution. The upper Panel of Table 3.1 summarizes the unconditional evolution of the different regional

[6]See the Data Appendix 6.2.1 for more details on the sample selection and the basic processing of the SIAB-R.

wage inequality measures between 1979 and 2006.[7]

In order to construct regional control variables, we include information from the Establishment History Panel (BHP), a 50 percent sample of all establishments throughout Germany with at least one employee liable to social security, stratified by establishment size (Gruhl et al., 2012). The additional covariates are chosen to control for the qualification structure as well as for the structural (firm size and industry composition) and demographic (gender and nationality) composition at the local level. Further, we include information on three basic area types (districts in urban, conurban and rural areas), following a classification scheme by the German Federal Office for Building and Regional Planning (BBR). Descriptive statistics for the regional covariates are summarized in the lowest Panel of Table 3.1.

3.3.2 Measuring Task Supplies

Construction and Trends

The information on task requirements of employees is derived from the BIBB/IAB Qualification and Career Survey (QCS). The BIBB comprises five cross sections launched in 1979, 1985, 1992, 1998 and 2006, each covering approximately 30,000 individuals (Rohrbach-Schmidt, 2009). The dataset is particularly well suited for our research, as it includes detailed information on the activities individuals perform at the workplace. For each individual i, these activities are pooled into three task categories: (1) non-routine cognitive, (2) routine and (3) non-routine manual tasks. In the assignment of tasks, we follow Spitz-Oener (2006) and construct individual task measures TM_i^j for task j and time t according to the definition of Antonczyk et al. (2009):

$$TM_{it}^j = \frac{\text{number of activities in category } j \text{ performed by } i \text{ in } t}{\text{total number of activities performed by } i \text{ over all categories in } t} \times 100, \qquad (3.8)$$

where $j = C$ (non-routine cognitive), R (routine) and M (non-routine manual) and $t = 1979$, 1985, 1992, 1998 and 2006. In order to match the task information to the SIAB-R, the individual task measures are aggregated at the occupational level, where the task input of individual i in occupation k at time t is weighted by its respective weekly working hours (L_{ikt}):

$$TI_{kt}^j = \left(\sum_i \left[L_{ikt} \times TM_{ikt}^j \right] \right) \left(\sum_i L_{ikt} \right)^{-1}. \qquad (3.9)$$

Table 3.2 provides an overview of the occupations with the highest non-routine cognitive, routine and non-routine manual task contents in 1979. The most routine intensive occupations include clerical and administrative occupations as well as blue-collar production occupations. Non-routine manual task intensive occupations include less-skilled service occupations

[7]These numbers are similar to data provided by official OECD and EU statistics.

Table 3.1: Descriptive Statistics on the Regional Level of Variables Employed

Variable	1979	1985	1992	1998	2006
Wage inequality measures					
Gini coefficient	.213	.219	.229	.242	.281
	(.010)	(.017)	(.017)	(.022)	(.028)
Theil index	.080	.086	.094	.106	.142
	(.014)	(.014)	(.014)	(.019)	(.028)
Log mean wage	4.181	4.195	4.334	4.339	4.331
	(.083)	(.086)	(.089)	(.087)	(.103)
Log P85/P15 ratio	1.181	1.186	1.182	1.189	1.231
	(.019)	(.020)	(.019)	(.020)	(.026)
Average task shares					
Non-routine cognitive (T^C)	.072	.021	.076	.136	.219
	(.011)	(.022)	(.020)	(.028)	(.026)
Non-routine manual (T^M)	.416	.406	.386	.388	.388
	(.025)	(.020)	(.023)	(.017)	(.014)
Routine (T^R)	.512	.574	.538	.475	.393
	(.020)	(.020)	(.024)	(.028)	(.022)
Relative task compensation					
Non-routine cognitive (W^C)	1.359	1.334	1.402	1.405	1.398
	(.123)	(.117)	(.139)	(.119)	(.196)
Non-routine manual (W^M)	.920	1.013	.995	.884	.693
	(.085)	(.108)	(.114)	(.141)	(.211)
Main explanatory variable					
Routine share	.416	–	–	–	–
	(.038)	–	–	–	–
Covariates					
Fraction female employees	.330	.328	.332	.325	.323
	(.045)	(.043)	(.038)	(.037)	(.038)
Fraction foreign employees	.081	.066	.090	.080	.108
	(.048)	(.039)	(.044)	(.041)	(.052)
Share manufacturing	.439	.428	.416	.385	.354
	(.125)	(.127)	(0.120)	(0.116)	(0.118)
Fraction high-skilled employees	0.027	0.035	0.046	0.059	0.074
	(.014)	(.017)	(0.022)	(0.027)	(0.034)
Fraction medium-skilled employees	0.679	0.724	0.759	0.783	0.804
	(.054)	(.051)	(0.044)	(0.041)	(0.041)
Fraction low-skilled employees	0.294	0.242	0.195	0.158	0.122
	(.058)	(.054)	(0.045)	(0.039)	(0.036)
Fraction small firms (<25 employees)	0.339	0.354	0.345	0.374	0.377
	(.083)	(.085)	(0.076)	(0.074)	(0.077)
Average region population	297,494	296,688	305,698	308,443	313,296
	(376,437)	(393,948)	(374,855)	(348,248)	(359,030)
Population density	301	299	311	316	317
	(418)	(403)	(415)	(408)	(400)

Notes: $N = 204$ labor market regions. Standard deviations in parentheses. Descriptives are depicted for years in which task information is available from BIBB/IAB data. All employment variables are based upon full-time employment subject to social security contributions for a given region. Fractions are computed with respect to total full-time employment. Task compensation is in constant 2000 Euro, corresponds to log daily returns and is expressed relative to the compensation for routine tasks.

(e.g. nursing assistants, waiters) as well as construction occupations (e.g. roofers). In contrast, occupations with a high non-routine cognitive task content include high-education occupations, such as teachers, engineers and scientists. Table 3.2 also shows the task shares of the respective occupations in 2006. Strikingly, the relative task intensities vary substantially over time. Particularly the group of routine intensive occupations has witnessed substantial changes in the distribution, presumably as a consequence of technological progress itself. Due to this large within-occupational variation, it bears notice that the natural dimension to test the predictions of the task-based framework is to explore direct changes in regional task inputs instead of occupational shifts.

Table 3.2: Ranking of Occupations According to their Task Content in 1979 and their Task Intensities

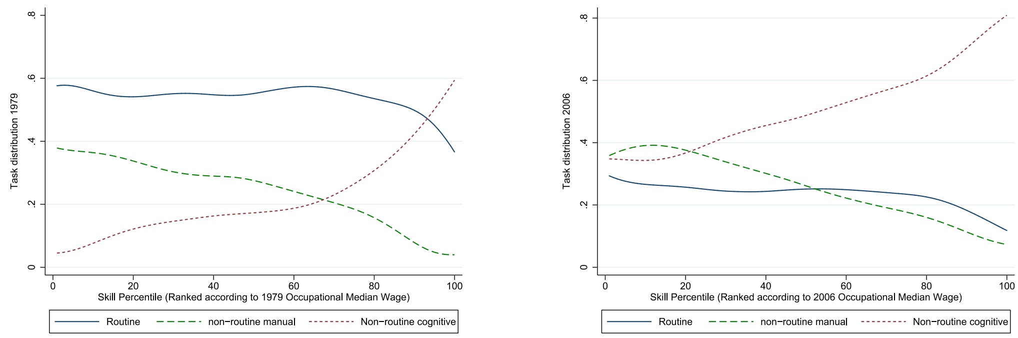
	1979			2006		
Occupation	abstract	routine	manual	abstract	routine	manual
Five occupations with highest non-routine cognitive task intensity in 1979						
Technical draughtpersons	0.90	0.10	0.00	0.88	0.12	0.00
University teachers	0.76	0.20	0.04	0.82	0.09	0.09
Mechanical, motor engineers	0.75	0.20	0.05	0.84	0.13	0.03
Electrical engineers	0.69	0.26	0.05	0.72	0.20	0.08
Survey engineers	0.66	0.29	0.05	0.77	0.17	0.06
Five occupations with highest routine task intensity in 1979						
Cashiers	0.03	0.95	0.02	0.67	0.07	0.26
Office auxiliary workers	0.06	0.91	0.04	0.59	0.13	0.28
Stenographers, data typists	0.07	0.91	0.02	0.76	0.03	0.20
Cost accountants	0.09	0.90	0.01	0.81	0.10	0.09
Post masters	0.08	0.88	0.03	0.57	0.08	0.35
Five occupations with highest non-routine manual task intensity in 1979						
Household and building cleaners	0.01	0.09	0.90	0.19	0.05	0.75
Nurses, midwives	0.12	0.14	0.75	0.46	0.16	0.38
Nursing assistants	0.08	0.18	0.74	0.34	0.14	0.52
Mechanics	0.10	0.19	0.72	0.28	0.39	0.33
Attending on guests	0.07	0.21	0.71	0.48	0.22	0.30

Notes: Task intensities are derived from BIBB/IAB data in 1979 and 2006 as defined in equation 3.9. The sample includes full-time employees between 20 and 60 years of age working in West-Germany, excluding agricultural and public sector employment.

Figure 3.2 provides stylized evidence on the systematic association between task intensities and their prevalence across the skill distribution. It plots the distribution of task usage across the skill distribution for 1979 and 2006, which is approximated by the occupational median wage in the respective year. The figure shows that non-routine cognitive tasks are prevalent in occupations at the top of the skill distribution. In contrast, routine and non-routine manual tasks are mainly performed by less-skilled employees. Interestingly, apart from a large level shift, this distributional pattern remains relatively stable over the entire period.

Regional Quantities and Prices

To obtain task measures at the regional level, the occupational task information from the QCS is matched to the SIAB-R, exploiting the fact that both datasets employ a time-consistent



(a) Task intensity 1979

(b) Task intensity 2006

Figure 3.2: Task Intensity Along the Wage Distribution, 1979 and 2006

Notes: Share of workers performing routine, non-routine manual and non-routine cognitive tasks in 1979 and 2006, respectively. Occupations are ranked according to their median wage in the respective year using the SIAB-R. Task intensity is derived from BIBB and defined as in equation 3.9.

definition of occupational titles according to the three-digit 1988 occupational classification provided by the Federal Employment Agency.[8]

We construct composition-adjusted region-level task shares following Peri and Sparber (2009). That is, we clean the task information of demographic characteristics, which may affect regional task supply and hence be correlated with the routine share. To do so, we regress separately by BIBB wave an individual's task supply TI_{kt}^{j} (derived from the occupation) on a gender dummy, potential experience and its square, a set of education fixed effects and a dummy indicating German nationality.[9] The region-level averages of the predicted values, weighted by the length of the respective employment spell, constitute the task supplies T_{rt}^{j} for each region r and year t. Summary statistics of the three task shares are displayed in Table 3.1. In line with the predictions of the task-based approach, we observe a general downward trend of routine task input over time. Simultaneously, the share of labor that performs non-routine cognitive tasks is increasing, while non-routine manual task inputs remain relatively constant over time.

To obtain regional task compensation measures for each year, we follow a two step procedure proposed by Peri and Sparber (2009). First, we construct average log wages in each region that control for observable differences in demographic characteristics across local labor markets. To obtain these *cleaned* wages we regress separately for each BIBB wave log real daily wages on the same variables that are used for the adjustment of the task

[8]Due to data protection reasons the SIAB-R is anonymized and occupational information is aggregated to 120 occupation groups. However, occupations are unambiguously assignable to the three-digit 1988 occupational classification.

[9]We calculate potential experience as current year minus year of birth minus age at the end of educational/vocational training. The average age for each education level is set at 15 for individuals "without completed education", 16 for those "without A-levels and without vocational training", 19 for those "without A-levels but with vocational training" or "with A-levels but without vocational training", 22 for those "with A-level and vocational training" and 25 for those "with a (technical) college degree". The results are available from the authors upon request.

variables. The regressions further include occupation by region dummies whose coefficients represent the estimates for the average cleaned log-wage, $\ln(\tilde{w}_{krt})$, for occupation k, region r and year t. In a second step, these cleaned wages are transformed into levels and regressed on the occupation-specific task intensities TI^{j}_{kt}. By separately estimating the second-stage regression described by equation 3.10 for each BIBB wave, we can identify the region and year-specific task compensations, w^{C}_{rt}, w^{R}_{rt} and w^{M}_{rt}, received for supplying one unit of non-routine cognitive, routine and non-routine manual tasks.

$$\tilde{w}_{krt} = w^{C}_{rt} \times TI^{C}_{kt} + w^{R}_{rt} \times TI^{R}_{kt} + w^{M}_{rt} \times TI^{M}_{kt} + e_{krt}. \tag{3.10}$$

Table 3.1 depicts the evolution of the compensation for non-routine cognitive and non-routine manual tasks relative to the compensation for routine tasks for each BIBB wave. As predicted by the AD framework, non-routine cognitive tasks experience relative wage gains over time. Yet, relative wages paid to non-routine manual tasks deteriorate after the 1980's.

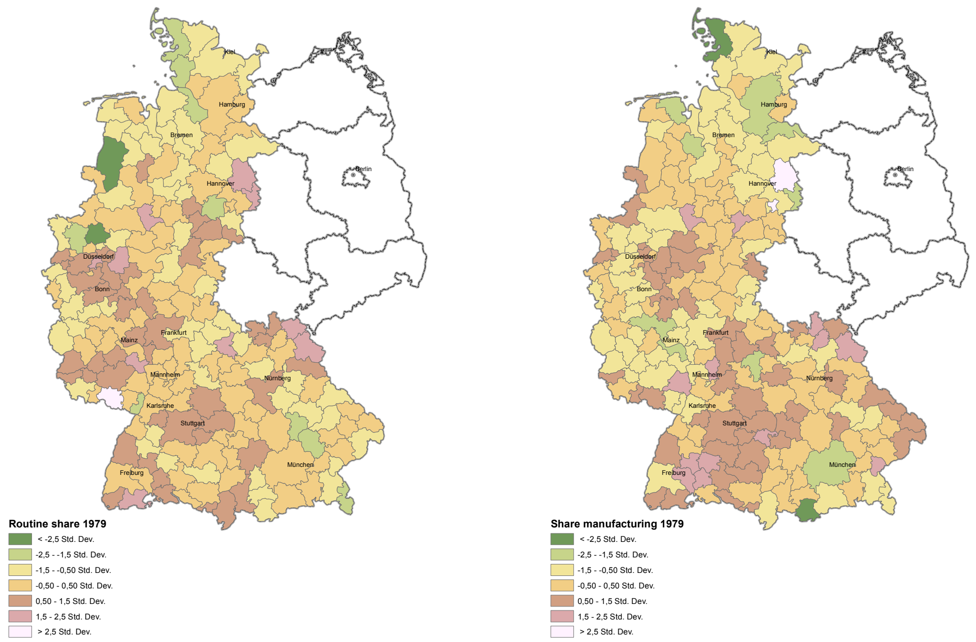
3.3.3 Measuring Technology Exposure

Our main explanatory variable is a measure that reflects the regional exposure to technological progress. Following AD, we generate this measure by using the occupational routine task index in 1979 (TI^{R}_{k1979}) to identify the set of occupations that are in the upper third of the routine task distribution.[10] We calculate for each labor market r the routine employment share, RSH_r, for the year 1979, equal to:

$$RSH_r = \left(\sum_k L_{kr} \times \mathbb{I}\left[TI^{R}_{k} > TI^{R,P66}_{k} \right] \right) \left(\sum_k L_{kr} \right)^{-1}, \tag{3.11}$$

where L_{krt} is employment in occupation k in labor market r in 1979, and $\mathbb{I}[\cdot]$ is an indicator function, which takes the value one if an occupation is routine intensive. The average population weighted regional routine share in 1979 is .42. A region at the 85th percentile of the routine share distribution has a 8.1 percentage points higher routine intensity compared to a region at the 15th percentile ($RSH^{P15} = .379$, $RSH^{P85} = .460$). To get an impression of the regional variation in routinization exposure, Figure 3.3a maps the geographic distribution of the regional routine intensity in 1979 across Germany. Routine intensive labor markets are industrial strongholds, such as Wuppertal and Wolfsburg, as well as human capital intensive regions, such as Düsseldorf, Bonn and Wiesbaden. Regions with a low routine share tend to be specialized in the tourism and hospitality industry and are often located near the Alps or the sea, such as Husum or Garmisch-Patenkirchen. A potential concern is that the routine share largely reflects the degree to which labor markets are specialized in manufacturing industries. In this case, it would be difficult to disentangle the impact of technology from trade-related explanations. The simple population-weighted correlation coefficient between technology

[10] Our results remain unchanged if we instead use occupations in the upper quarter or upper half of the routine task distribution. Results are available from the authors upon request.



(a) Routine Share (b) Share Manufacturing

Figure 3.3: Distribution of Routine and Manufacturing Share in 1979

exposure and the manufacturing share is moderate and amounts to .255, indicating that the routine share is more related to the production technology than to industry specialization. As a visualization, Figure 3.3b shows the distribution of the manufacturing share across German regions.

3.4 Results

3.4.1 Technology and Task Supply

We now turn to the main estimates of the impact of technological change on regional task structures, compensation patterns and overall wage inequality. As a first step, we focus on changes in regional task structures by fitting the following variant of equation 3.7:

$$\Delta T^{j}_{r,1979-2006} = \alpha + \beta_1 RSH_r + \mathbf{X_r}'\beta_2 + \gamma_s + e_r, \tag{3.12}$$

where the dependent variable is the change in the supply of task j between 1979 and 2006 in labor market r, where $j = \text{R}$, C and M. The estimates from weighted-least squares regressions (WLS) are presented in Table 3.3. As a baseline, the first column presents a specification with the regional routine share as the variable of interest and a full set of state dummies. The estimated effect of technology on routine tasks is negative and significant at the 1 percent level, implying that regions that were particularly exposed to technology experienced greater declines in routine tasks.

Table 3.3: Technology and Task Supply, 1979-2006

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: ΔT^R			
RSH_{1979}	-.359***	-.315***	-.327***	-.439***	-.232***	-.401***
	(.070)	(.064)	(.054)	(.035)	(.063)	(.035)
Rural area		.032***				.007*
		(.006)				(.004)
Conurban area		.037***				.006
		(.007)				(.004)
High-skilled			-1.020***			-.356***
			(.126)			(.126)
Low-skilled			.119***			.016
			(.037)			(.033)
Manufacturing empl.				.161***		.133***
				(.015)		(.017)
Empl. in small estbl.				.236***		.101***
				(.022)		(.025)
Female employment					-.011	.115***
					(.054)	(.036)
Foreign employment					-.369***	-.161***
					(.071)	(.038)
R^2	.380	.520	.765	.783	.546	.848
			Panel B: ΔT^C			
RSH_{1979}	.091	.053	.063	.185***	-.040	.128***
	(.064)	(.063)	(.043)	(.035)	(.063)	(.036)
R^2	.160	.308	.681	.686	.374	.778
			Panel C: ΔT^M			
RSH_{1979}	.267***	.262***	.265***	.255***	.272***	.273***
	(.027)	(.026)	(.028)	(.024)	(.028)	(.026)
R^2	.603	.619	.605	.624	.619	.638

Notes: N=204 labor market regions. All models include dummies for the federal state in which the region is located and regional covariates as indicated as well as a constant. Models are weighted by start of period share of national population. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

To control for other factors that may explain regional changes in the task supplies, we augment the model step-by-step with a number of additional explanatory variables. In column 2, we control for differences in the degree of urbanization across regions by adding information on regions' area type. Numerous studies have found evidence for significant productivity differences between urban and rural areas due to agglomeration economies (Bacolod et al., 2009; Glaeser and Resseger, 2010; Davis and Dingel, 2012). Hence, it is likely that also task requirements evolve differently in regions of different types. Indeed, the decline in routine task inputs is significantly less pronounced in rural and conurban regions (as compared to urban areas which constitute the baseline category).

To capture differences in the regional human capital structure, column 3 adds the share of high-skilled and low-skilled employees in the local labor force. While regions with large shares of low-skilled employees witness smaller declines in routine task requirements, a greater initial supply of high-skilled employees predicts declining routine task inputs. In column 4, we further include two variables that reflect local economic conditions: the share of small establishments (< 25 employees), which may lead to regional productivity disparities (Agrawal et al., 2014) and the share of employment in manufacturing. Both variables enter with a positive sign, predicting an increase in the subsequent input of routine tasks. Finally, column 5 considers the share of female employees and the share of foreigners in the local labor force. Both variables are associated with declining regional routine task requirements, although the coefficient on female employment is imprecisely estimated.

Notably, the inclusion of additional explanatory variables leaves the significant, negative relationship between technology exposure and routine task inputs largely unaffected. When all control variables are simultaneously included (column 6), the point estimate increases slightly and the precision of the point estimate rises. To interpret the coefficient, we compare a region at the 85th percentile with a region at the 15th percentile of the routine share distribution in 1979 and predict their respective change in the input of routine tasks. The point estimate of -.401 implies a differential decline in routine tasks by 3.2 percentage points relative to a mean decrease of 11.9 percentage points between 1979 and 2006. Panel B and C present the results for the change in non-routine cognitive and non-routine manual tasks between 1979 and 2006. The estimates on both task inputs are positive and statistically significant.

To test whether the observed patterns are consistent over time, we estimate models described by equation 3.12 separately for each outcome year and depict the results in Table 3.4. The year 1979 remains the base year, such that the coefficients reflect how the impact of technology accumulates over time. The effect of technology on routine tasks is negative and statistically significant in all sample years after 1979, and most pronounced during the 1990's. Similarly, both non-routine task inputs have experienced a differential growth in initially routine intensive regions throughout the observation period. The coefficients increase, indicating that the adaption in task inputs as a result of technological change is a continuous process. However, it is noteworthy that the impact of computerization on the regional task structure attenuates over time, since the coefficients on the routine task share remain relatively stable in the later periods (columns 3 and 4).

In order to detect possible heterogeneous effects of technology exposure across demographic groups, Panel A of Appendix Table 6.2 depicts regressions bifurcated by gender, age and education level. The estimated coefficients indicate that the effects of computerization are similar in magnitude across all subsamples. One group exempted from the general pattern are high-skilled employees, among whom computerization has left the requirements for non-routine manual tasks unaffected. Instead, they exclusively increase their input of non-routine cognitive tasks, which is consistent with theoretical considerations in AD.

The results of our analysis so far strongly support the key implications of the task-based

Table 3.4: Technology and Task Inputs, Subperiods

Time period:	1979-1985 (1)	1979-1992 (2)	1979-1998 (3)	1979-2006 (4)
		Panel A: ΔT^R		
RSH_{1979}	-.264***	-.283***	-.402***	-.401***
	(.028)	(.030)	(.040)	(.035)
R^2	.674	.693	.847	.848
		Panel B: ΔT^C		
RSH_{1979}	.098***	.114***	.159***	.128***
	(.023)	(.021)	(.033)	(.036)
R^2	.731	.706	.820	.778
		Panel C: ΔT^M		
RSH_{1979}	.166***	.169***	.243***	.273***
	(.022)	(.023)	(.026)	(.026)
R^2	.516	.330	.614	.638

Notes: N=204 labor market regions. All models include dummies for the federal state in which the region is located and covariates reflecting the human capital and demographic composition outlined in column (6), Table 3.3 as well as a constant. Models are weighted by start of period share of national population. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

approach, providing evidence for increasing specialization of employees in non-routine tasks as a consequence of routine task substituting technological change.

3.4.2 Technology and Tasks Compensation

We now explore whether the changes in the regional task structure are accompanied by corresponding changes in the compensation paid to different tasks. To do so, we estimate the following model:

$$\Delta ln(\widehat{w}_r^j) = \alpha + \beta_1 RSH_r + \mathbf{X_r'}\beta_2 + \gamma_s + e_r. \tag{3.13}$$

The dependent variable represents the estimated change in the log compensation paid to task $j = R, C$ and M between the base year 1979 and each of the following BIBB waves. Task compensation estimates are acquired for each labor market and year according to the methodology described in section 3.3.2. Table 3.5 reports the coefficient on the regional routine share. The results on the vector of control variables are omitted due to space constraints.

In line with the theoretical model, the WLS estimates in Panel A of Table 3.5 indicate that technological change had an adverse effect on the compensation of routine tasks. The estimated coefficients are negative in the last three periods. However, it bears notice that this relationship is imprecisely estimated for the overall observation period from 1979 through 2006.

Table 3.5: Technology and Task Compensation, Subperiods

Time period:	1979-1985 (1)	1979-1992 (2)	1979-1998 (3)	1979-2006 (4)
		Panel A: $\Delta ln(\widehat{w}^R)$		
RSH_{1979}	.015	-.202*	-.227*	-.362
	(.083)	(.109)	(.118)	(.272)
R^2	.298	.232	.343	.269
		Panel B: $\Delta ln(\widehat{w}^C)$		
RSH_{1979}	.198	.322**	.301**	.404**
	(.133)	(.137)	(.132)	(.174)
R^2	.367	.413	.522	.547
		Panel C: $\Delta ln(\widehat{w}^M)$		
RSH_{1979}	-0.216**	-0.208*	-0.260*	-.701
	(.094)	(.113)	(.133)	(.460)
R^2	.272	.354	.352	.396

Notes: N=204 labor market regions. All models include dummies for the federal state in which the region is located and covariates reflecting the human capital and demographic composition outlined in column (6), Table 3.3 as well as a constant. Models are weighted by start of period share of national population. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

Panel B and C present complementary estimates for the wages paid to non-routine cognitive and non-routine manual tasks. Regions with a high technology exposure witnessed significant increases in the compensation of non-routine cognitive tasks. The coefficient of .404 implies a differential wage increase of 3.3% between a region at the 85th and the 15th percentile of the routine share distribution through 1979 to 2006. With respect to the dynamic pattern of the effect, the estimates suggest that the effect was strongest until the beginning of the 1990's (columns 1 and 2) and increased only slightly thereafter (columns 3 and 4). The estimates in Panel C indicate that the compensation for non-routine manual tasks has decreased differentially in regions which were initially specialized in routine intensive employment. In contrast to the results obtained for the other tasks, the dynamic pattern reveals that the effect of technology has accelerated over time, although the estimate is statistically not different from zero when considering the entire period (column 4). The point estimate of -.701 implies a differential wage decrease of 5.7% in a region at the 85th relative to a region at the 15th percentile between 1979 and 2006. The result that computerization decreases the compensation for non-routine manual tasks suggests that the rise in the supply of non-routine manual tasks was not met by a sufficient increase in the demand for these tasks to offset negative wage effects. This finding stands in contrast to results for the US as presented by AD, who document employment *and* earnings growth for occupations that are characterized by a high non-routine manual task content.

Panel B of Appendix Table 6.2 reports the coefficients of the models that are estimated separately by gender, age and education. In the case of high-skilled employees, some region-occupation cells have very few observations. Hence, we report the results for this subgroup only for the sake of completeness, but they are to be interpreted cautiously. While the results for older and younger employees are relatively similar, some substantial differences between changes in compensation patterns for males and females can be detected.

3.5 Regional Wage Inequality

So far, our empirical analysis has found a robust relationship between the historical exposure to technological change and subsequent changes in the structure and compensation of tasks across regions. Can these findings help understanding the roots of increasing wage inequality within and across regions? Recall that there exists a systematic association between the prevalence of tasks across the skill distribution. That is, non-routine cognitive tasks are prevalent at the upper tail of the wage distribution, whilst routine and non-routine manual tasks are predominantly performed at lower parts. Hence, technological change should lead to an increases in wage inequality within regions.

Figure 3.4 presents some descriptive evidence on this prediction by plotting unconditional log wage changes between 1979 and 2006 at each percentile of the wage distribution for two sets of regions: those with an above average routine share in 1979 and those with a routine share below it. As shown, wages grew more at the upper part of the wage distribution in both sets of regions. Yet, it is noticeable that the increase in wage inequality is much more pronounced in routine intensive regions. For example, wages at the 85th percentile have grown 8 percentage points more over the observed period in routine intensive regions.

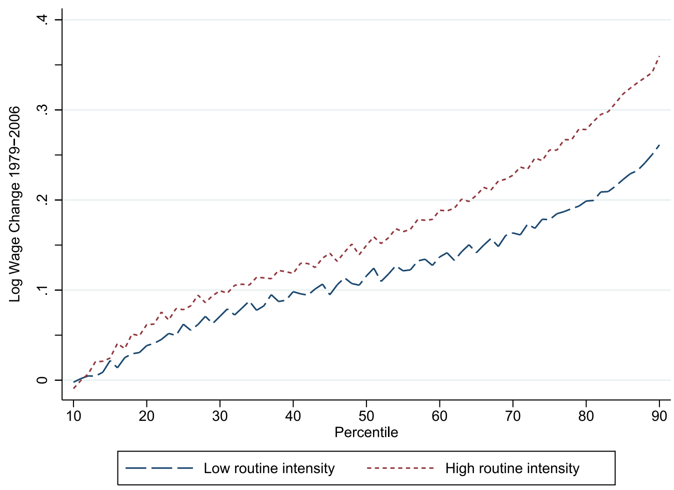


Figure 3.4: Wage Change by Percentile, 1979-2006

Notes: Notes: Figure plots unconditional log wage changes between 1979 and 2006 at each percentile of the wage distribution in regions with high and low routine intensities in 1979. Percentile numbers refer to wage distribution in 1979.

To inspect the link between technology exposure and wage inequality in more detail, we

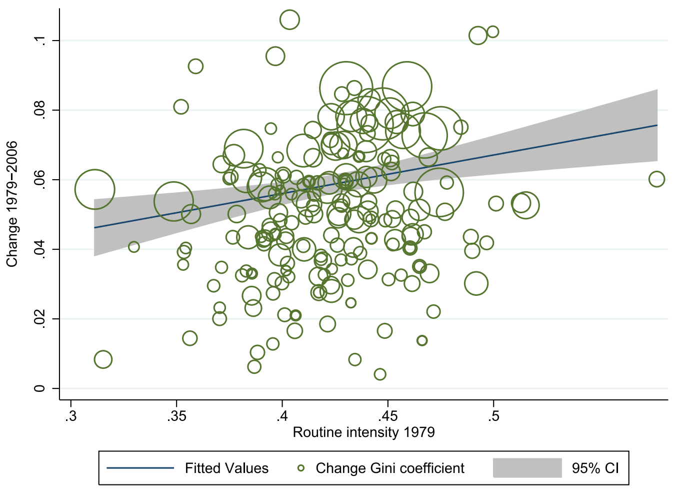


Figure 3.5: Change in Gini-Coefficient between 1979 and 2006 versus Routine Intensity in 1979

Notes: Figure plots routine intensity in 1979 against the change in Gini-coefficient for 204 local labor markets. The size of the circles is proportional to the regional population in 1979. The line is the predicted change in the Gini coefficient from a weighted OLS regression, where the weights are the regional population in 1979. The slope is .111 (.032).

perform an econometric analysis, where income dispersion across local labor markets is measured by the Gini-index. The scatterplot in Figure 3.5 depicts the bivariate relationship between the local routine share in 1979 and changes in the Gini-coefficient over the subsequent 27 years and provides initial support for the prediction that technological change has contributed to rising wage inequality. The positively sloped regression line corresponds to the following WLS regression of the change in the Gini-coefficient between 1979 and 2006 on the routine share, where weights are equal to the regional population in 1979:

$$\Delta Gini_{r,1979-2006} = 0.01 + 0.11 \times RSH_r + e_r, \quad se = 0.032 \quad n = 204 \tag{3.14}$$

The positive coefficient implies that the Gini-index rose by 21.3% more in a region at the 85th percentile compared to a region at the 15th percentile, indicating that the economic significance of the estimate is substantial.[11] Figure 3.6 provides some evidence on the dynamics of the routinization effect, plotting estimated coefficients on an annual basis for the years 1980 through 2006. The equations underlying this figure are identical to a version of equation 3.14, where the model is augmented by the full set of controls used in earlier specifications and estimated separately for each year. Until the mid 1980's, the estimated effect is small in magnitude and statistically not different from zero. Starting from that, the coefficient on technology exposure is positive and statistically significant in almost all years. With respect to the time pattern, the estimates reveal that the effect of technological

[11]This number is calculated by dividing the 85th/15th percentile difference of .9 percentage points by the predicted increase in the Gini-index at the 15th percentile of the distribution.

change on the evolution of wage inequality roughly doubles during the 1990's, and decreases thereafter. To test the robustness of our results, we also estimated the computerization effect on alternative wage inequality measures (Theil-index and 85th/15th percentile wage ratio). As shown in Appendix Figure 6.2, the estimated coefficients reveal that the results do not hinge on a particular inequality measure.

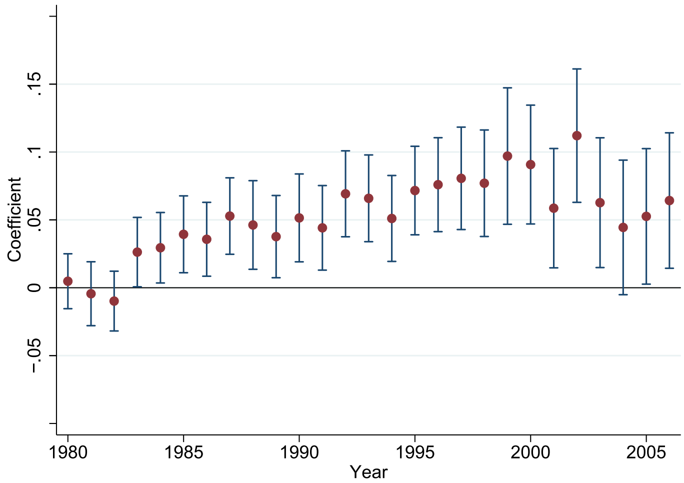


Figure 3.6: Estimated Impact of Technological Change on the Gini-Coefficient

Notes: The figure plots the regression coefficients and 90% confidence intervals obtained from up to 26 regressions. The regressions relate the Gini-index during the year indicated, to the regional technology exposure. All regressions include covariates reflecting the human capital and demographic composition outlined in column (6), Table 3.3.

3.5.1 Dispersion Analysis

As discussed in the Introduction, wage inequality has not only increased within regions, but also to differential degrees across space. It is therefore important to ask whether differences in technology exposure can help understanding the variation of wage inequality growth across German regions. To answer this question, we perform a simple counterfactual exercise. Specifically, we predict changes in the Gini-coefficient between 1979 and 2006, when only one component of regional wage developments is allowed to vary:

$$\Delta\widehat{Gini_r} = \alpha + \beta_1 RSH_r + \beta_2 \overline{X}. \tag{3.15}$$

Then, $\Delta\widehat{Gini_r}$ is the change in the Gini-index that would prevail if the considered region r differed from the regional average ($\overline{X}$) only with respect to its task structure. We perform this exercise analogously for the other explanatory variables in our model. Thus, we obtain predicted changes in wage inequality when we allow for variation in economic conditions (firm sizes and industry structure), the qualification structure and the demographic composition (share of female and share of foreign employees), as well as the area type.[12] For each of these variables, Table 3.6 displays the highest and the lowest predicted change in the Gini-coefficient as well as its difference.

Table 3.6: Results of the Dispersion Analysis

	Technology Exposure (1)	Qualification (2)	Economic (3)	Demographic (4)	Urbanity (5)
Min	.044	.034	.035	.048	.045
Max	.059	.073	.062	.052	.052
Range	.015	.039	.027	.004	.007

Notes: N=204 labor market regions. Each column represents the smallest and largest predicted change in the regional Gini-coefficient between 1979 and 2006 when only the indicated determinant of regional wage developments is allowed to vary.

The results indicate that most regional disparities in wage inequalities are generated by the economic components, followed by the qualification structure. The contribution of technological change is the third most important source of wage dispersion across regions, whereas the demographic composition and the area type of local labor markets are least important for explaining wage dispersion across spatial units.

3.6 Conclusion

This chapter examines the spatial dimension of labor market inequality in Germany in recent decades at the level of local labor markets focusing on the role of technological change. The analysis builds on concepts of the task-based view of technological progress which has proven to be successful in explaining wage and employment trends at the aggregate level. We document substantial differences in both, the evolution of labor market inequality across space and the degree to which regions are exposed to technology. We show that regions that were prone to computerization witnessed a more pronounced relocation from routine to non-routine task inputs together with differential changes in task compensation. Despite rising non-routine cognitive task inputs, wages paid to these tasks have increased suggesting that the demand for them has risen faster than the supply. On the contrary, increases in the input of non-routine manual tasks were accompanied by wage decreases. While the negative compensation effect of routine tasks is limited to the early 1980's and 1990's, it is attenuated over time and becomes insignificant thereafter. These developments translate into the regional wage structure resulting in an increase in wage inequality within and between labor markets, driven by opposing dynamics at both tails of the wage distribution. The findings of this study complement existing empirical literature that has primarily focused on deunionization as the main explanatory factor for recent developments at the lower tail of the

[12] It bears notice that since the effects are not orthogonal, the sum of the partial effects is not equal to the overall change in a region's Gini-coefficient.

German wage distribution.

Thus, our study underlines the importance of demand side factors when exploring the impact of technological change on wage and employment patterns. Contrary to the US, technological progress did not benefit low-paid employees in Germany implying that demand for non-routine manual tasks has not risen sufficiently to offset the decline in wages induced by technological change.

4 Product Market Deregulation and Employment Outcomes: Evidence from the German Retail Sector

4.1 Introduction

It is a well established fact that the regulatory environment of product markets has an impact on labor market outcomes. In this context, the deregulation of product markets is often mentioned as a promising means to foster employment growth. While the majority of existing empirical literature indeed finds positive labor market effects of deregulation (e.g. Bertrand and Kramarz (2002)), the present analysis shows that the post-liberalization path of employment can, as well, take an unfavorable course.

I study the deregulation of the retail sector in Germany resulting from a reform of shop closing legislation in 2006 and 2007. Within the realm of the reform of federalism (*Föderalismusreform*), adopted by the Federal Parliament and the Federal Council in 2006, legislative power on shop closing laws was conferred upon the federal states. This initiative marked the beginning of a period of extensive deregulation in which 14 German federal states liberalized their trading provisions. To uncover the employment effects of the reform, I exploit regional variation in trading provisions across the German states. When using spatial variation in policies, the issue of endogeneity is central (Besley and Case, 2000): If deregulation responds to economic and political conditions, it will not be exogenous and estimates of the liberalization effect will be biased. In the specific context, however, the decision of the non-deregulating state government in Bavaria to retain the previously effective federal law was made incidentally. Hence, this policy reform represents a natural experiment that can be used to identify the causal effect of the liberalization of shop closing laws.

I present evidence that the deregulation of shop closing legislation had a negative effect on aggregate retail employment. In quantitative terms, the coefficient estimate suggests that liberalization is associated with a moderate loss of 19,000 full-time equivalent jobs. In addition, this study sheds light on the transmission channel of the reform. First of all, I show that losses were mainly borne by full-time employees, while part-time employment was unaffected. Secondly, deregulation induced a change in the market structure by significantly decreasing the number of small retail stores. Thirdly, evidence for increased revenues or significant declines in prices, as was hoped for by policymakers by the time, could not be found. Taken together, these results explain why the aggregate effect on employment is negative: deregulation has not led to a post-liberalization output boom, but instead caused a redistribution of sales from small towards larger establishments, which are relatively less personnel-intensive than small formats.

While these results stand in contrast to the majority of existing empirical literature in this field, it bears notice that, from a theoretical perspective, the sectoral employment effect of deregulation is ambiguous (Blanchard, 2006). As deregulation increases productivity, less employment is needed for a given level of output. In particular, if a regulated environment facilitates the creation of X-inefficiencies with overstaffed operating levels, employment decreases after deregulation. Yet, if liberalization-induced productivity gains decrease prices, final demand and output rise, eventually increasing labor demand. Therefore, the question how deregulation affects employment is ultimately an empirical one.

A number of theoretical studies is concerned with the question how deregulation affects market structures. Although shop closing regulations were most often designed for religious reasons and in order to protect employees in the retail sector, they tend to favor small retailing units. First of all, restrictive opening hours reduce returns on investment. As large retailers have higher investments in real estate and inventories, they are more heavily affected by regulation (Pilat, 1997). Secondly, in the presence of restrictive closing laws, consumers have less time to drive to larger stores which are often located outside city centers, even if there are price differences between the formats (Tanguay et al., 1995). Thirdly, due to the need for threshold labor, i.e. the need for at least one person to be employed at all times a shop is open, it is more costly for small retailing units to extend opening hours than for large ones (Nooteboom, 1983). Wenzel (2011) generalizes these arguments and develops a theoretical model, where efficiency differences between large and small establishments result in asymmetric opening hours and eventually harm small formats. In a recent study, Haskel and Sadun (2012) empirically analyze whether there is evidence for productivity differences between shops of different sizes. Indeed, they find a strong association between the shift towards smaller stores and decreases in productivity growth.

Despite the intensity of the public debate on shop closing laws in Germany, the academic literature on this issue is relatively scarce and remains inconclusive. Täger et al. (2000) examine the implications of the federal reform of shop closing laws in 1996. The authors find that employment and turnover have developed positively, while competition among retailers has increased as a consequence of deregulation. In contrast, studies by Hilf and Jacobsen (1999; 2000) find that employment in the retail sector has not increased after the reform, but that working time arrangements of employees have worsened. Most importantly, the problem with existing studies is that they rely on a single source of variation in legal provisions to identify employment effects of deregulation. Thus, they lack an adequate control group that would help eliminate the impact of confounding factors on employment changes in retail. The present study overcomes this problem by exploiting regional variation in trading provisions. To my knowledge, the only study that uses a similar identification strategy is the paper by Bossler and Oberfichtner (2014) who focus on employment developments in a small subset of overall retailing.

This paper is closely related to a number of empirical studies that have analyzed the impact of product market regulations in the retail sector on employment outcomes. One of the first analyses was conducted by Bertrand and Kramarz (2002) who examine zoning laws in France which regulate the entry of large firms in the market. They find that this policy had a sizable adverse effect on retail employment, estimating that in absence of these laws, employment could have been approximately 10% higher. Further, the authors find that less stringent entry regulation leads to a significant decrease of employment in small shops. In a similar vein, Viviano (2008) shows that lower entry barriers for large stores led to higher employment in Italy, where additional employment is almost exclusively created in large stores. Yet, at least in the medium term, she does not find a significant negative employment effect of deregulation on small shops.

Skuterud (2005) analyzes the employment effects of changes in shop closing legislation by exploiting differences in provisions on Sunday trading across Canadian provinces. At the aggregate level, he finds evidence of modest employment gains, and decomposes this effect into positive threshold labor and sales effects and a negative effect on employment resulting from increased labor productivity. In a similar approach, Goos (2004) examines the impact of shop closing hours on employment and product markets in the United States. Using a difference-in-difference strategy, he shows that deregulation increases employment by 4.4 to 6.4 percent. Burda and Weil (2005) use changes in regulatory regimes in the period 1969-1993 to identify the employment effect of opening restrictions in the US. They find that Sunday closing regulation significantly reduces employment inside and outside the retail sector, with part-time employment being particularly affected. Though, a robust effect of closing laws on wages, prices and labor productivity was not found in the study.

This paper is also related to the literature on the displacement effects of large "Big-Box" retail establishments on smaller "Mom-and-Pop" stores. Haltiwanger et al. (2010) find substantial negative effects of Big-Box establishments on single unit and local chain stores. In a similar vein, a number of studies analyze the competitive effects of Wal-Mart stores on local competitors in the United States. Basker (2005) finds that Wal-Mart increases retail employment right after market entry. This positive effect decreases considerably over time, when some small and medium retailers close. Neumark et al. (2008) even find a negative effect of Wal-Mart on total retail employment. This result is supported by findings in Jia (2008), who reports that the expansion of Wal-Mart explains 50 to 70% of the net change in the number of small discount retailers.

The remainder of the paper is organized as follows. In the subsequent section, I describe the institutional background of the recent liberalization of shop closing legislation in Germany. In section 4.3, I present the estimation strategy, discuss identification issues and provide an overview of the data used in the analysis. The econometric analysis is conducted in sections 4.4 and 4.5. Section 4.6 concludes.

4.2 Legislation

The German retail sector was highly regulated for decades.[1] Since 1956, legislative power regarding shop opening hours lay with the federal government. The "Law Concerning Shop Closing Time" (*Gesetz über den Ladenschluss*) restricted opening hours of retail stores from 7 am to 6:30 pm on weekdays and from 7 am to 2 pm on Saturdays. Except from Sundays in the advent season, shop opening was generally prohibited on Sundays as well as on public holidays. Several amendments were made to the Law Concerning Shop Closing Time: In 1960, Sunday shopping before Christmas was abolished, and instead shopping hours on Saturdays in the advent season were extended. Further amendments concerned the extension of opening hours for shops in recreation localities in 1969 and for shops in train stations and airports in 1986 (Täger et al., 1995). Yet, despite a lively debate on the usefulness of restrictions of shop opening hours, the law was not fundamentally changed for three decades. The deregulation process began with the introduction of the "service evening" in 1989, allowing retail stores to open until 8:30 pm on Thursdays. Further relaxations followed in 1996 and 2003, according to which shops could remain open between 6 am and 8 pm on all weekdays and Saturdays.

In June and July 2006, the Federal Parliament and the Federal Council adopted a reform of federalism, as part of which the legislative power on shop closing issues was conferred upon the federal states. This marked the beginning of a period of extensive deregulation, in which 14 of the 16 German federal states liberalized their trading provisions. Berlin, Brandenburg, Hesse, North Rhine-Westphalia, Rhineland-Palatinate, Saxony-Anhalt and Thurangia were the first states to pass state laws in November 2006. Within five months, Schleswig-Holstein, Hamburg, Baden-Wurttemberg, Saxony, Bremen and Lower Saxony followed.[2] Mecklenburg-West Pomerania was the last of the states to enact new closing laws, doing so in July 2007. However, plans to liberalize shop opening restrictions were already stipulated in the coalition agreement of the state government in November 2006 (Coalition Agreement between CDU and SPD, 2006). Hence, it is unlikely that the lagged implementation reflects policy endogeneity.

Only Bavaria and the Saarland adhered to the initial regulation.[3] Notably, the decision of the Bavarian government not to deregulate shop closing laws was made capriciously, a fact that is important for the following econometric analysis. Before the reform, the Bavarian minister of economic affairs had emphasized Bavaria's pioneering role in the deregulation of shop closing laws (WaMS, 2006). Yet, the vote in the caucus which decided on the extensions resulted in a standoff because Prime Minister Edmund Stoiber had left the meeting early (SZ, 2006). As a consequence, the Bavarian government adhered to the restrictive closing laws

[1] For a comprehensive overview of the history of shop closing laws, see Täger et al. (1995) and Spiekermann (2004).

[2] As the dataset employed for the analysis contains yearly observations as of the 30th June of a given year, this policy variation by month is not exploited.

[3] While Bavaria didnt pass any state legislation at all, the Saarland adopted a state law concerning shop opening times which did not change provisions effective under federal law.

that were effective under Federal Law and decided to observe experiences made by other states before taking further action.[4]

The new state laws vary not only at the regional level but also differ with respect to the scope of liberalization. While nine out of 14 states abolished all opening restrictions on weekdays and on Saturdays, the remaining five retained some provisions. Also, regulations on Sunday trading differ across states. Detailed information on the enforcement dates of the state laws as well as on the provisions on shop opening is given in Table 4.1.

The legislative changes were subject to contentious political and public debate. With respect to the reform's costs and benefits, the most controversial issue was its expected labor demand effect.[5] Proponents viewed the deregulation as a means to boost sales and to create more jobs. These expectations were backed by a report of the expert advisory board (Deutscher Bundestag, 1995) and a simulation by the ifo institute, according to which an extension of shop opening hours from 6.30 pm to 10 pm would create 50.000 additional full-time jobs (1995, p. 328). In contrast, opponents of the reform feared a reduction of employment and a shift towards more part-time and casual work.

Table 4.1: Deregulation of Shop Opening Hours Legislation

Federal State	Introduction	Weekday	Saturday	Sunday	Scope
Baden-Wurttemberg	06. March 2007	0 am - 12 pm	0 am - 12 pm	3×5 hrs	.71
Bavaria	-	6 am - 8 pm	6 am - 8 pm	4×5 hrs	-
Berlin	14. November 2006	0 am - 12 pm	0 am - 12 pm	8×7 hrs	.72
Brandenburg	29. November 2006	0 am - 12 pm	0 am - 12 pm	6×7 hrs	.72
Bremen	01. April 2007	0 am - 12 pm	0 am - 12 pm	4×5 hrs	.71
Hamburg	01. January 2007	0 am - 12 pm	0 am - 12 pm	4×5 hrs	.71
Hesse	30. November 2006	0 am - 12 pm	0 am - 12 pm	4×6 hrs	.71
Lower Saxony	01. April 2007	0 am - 12 pm	0 am - 12 pm	4×6 hrs	.71
Mecklenburg-West Pomerania	16. July 2007	0 am - 10 pm	0 am - 10 pm	4×5 hrs	.69
North Rhine-Westphalia	21. November 2006	0 am - 12 pm	0 am - 12 pm	4×5 hrs	.71
Rhineland-Palatinate	29. November 2006	6 am - 10 pm	6 am - 10 pm	4×5 hrs	.14
Saarland	15. November 2006	6 am - 8 pm	6 am - 8 pm	4×5 hrs	-
Saxony	16. March 2007	6 am - 10 pm	6 am - 10 pm	4×6 hrs	.14
Saxony-Anhalt	30. November 2006	0 am - 12 pm	0 am - 8 pm	4×5 hrs	.66
Schleswig-Holstein	01. December 2006	0 am - 12 pm	0 am - 12 pm	4×5 hrs	.65
Thurangia	29. November 2006	0 am - 12 pm	0 am - 8 pm	4×6 hrs	.66
Federal law before reform	01. June 2003	6 am - 8 pm	6 am - 8 pm	4×5 hrs	-

Notes: Information on legislation is compiled from law texts. The scope of deregulation is defined as the percentage change in hours which shops are allowed to additionally open according to new state legislation.

In sum, two features of the legislative process provide the foundation for the identification strategy in the following empirical analysis. First of all, there exists regional variation in the

[4] A further particularity of the legislation process is that the deregulation decision was influenced by courts in some states. Liberalization opponents have repeatedly made efforts to take legal actions against state-level closing laws. For instance, the Christian churches in Berlin filed suits against plans to liberalize Sunday shopping throughout December, pleading constitutionally guaranteed Sunday rest. The Federal Constitutional Court ruled in favor of the liberalization opponents (BVerfG, 2009).

[5] Further arguments relate to the coordination of leisure, the protection of small retailers from large outlets and the need to meet changing consumer demands.

deregulation process which allows me to compare employment outcomes in federal states which lifted restrictions with federal states that did not. Secondly, this policy variation can be considered exogenous, as neither the decision of the state government of Bavaria not to deregulate nor the lagged enactment of the law in Mecklenburg-West Pomerania did reflect socio-economic particularities of the respective federal states.

4.3 Empirical Strategy and Data Description

4.3.1 Empirical Strategy and Identification

The quasi-experimental setting described in the previous section allows me to use a difference-in-difference strategy in order to gauge the causal effect of deregulation on employment in the retail sector. While the majority of federal states passed laws to deregulate opening restrictions in the years 2006 and 2007, two states adhered to federal law. The first group comprises the treatment group and the latter the control group. In the analysis, I contrast employment outcomes before and after the deregulation in the treatment group. The control group of non-deregulating states is needed to extract employment trends in the retail sector common to all federal states, as they would otherwise falsely be attributed to the extension of shop opening hours. In order to identify the employment effect of deregulation, I fit empirical models of the following type:

$$\ln Y_{dst} = \alpha + \beta_1 Dereg_{st} + \mathbf{X'_{dt}}\beta_2 + \gamma_d + \delta_t + \varepsilon_{dst}. \tag{4.1}$$

The main dependent variable Y_{dst} represents the fraction of retail sector employees in overall employment, calculated for each district d located in state s at time t. In order to analyze effect heterogeneity, I further divide overall retail employment into different subsets bifurcated by establishment size, working-time arrangement, or gender. In addition, I generate a dependent variable which reflects the number of small, medium and large shops in district d at time t. All dependent variables are expressed as natural logarithms.

$Dereg_{st}$ denotes a dummy variable equal to one if a district is located in a state s which has deregulated its shop closing law at time t and zero otherwise. Thus, β_1 is the parameter of interest and reflects the differential employment effect due to the deregulation of shopping hours. All estimates include a vector of district dummies, γ_d, which control for mean differences in retail employment across districts. Furthermore, the regressions include year dummies, δ_t, that control for aggregate time shocks. In extensions to this, I augment the model by time-varying district characteristics, X_{dt}, which may independently influence employment in retail. Further, I estimate specifications where the model described by equation 4.1 is enriched by linear as well as quadratic district-specific time trends. This modification allows for deviations from the common trend assumption, such that the identification of the deregulation effect results from whether the law change led to deviations from pre-existing trends.

One concern for the identification strategy is that unobserved determinants of retail employment growth may be correlated with the decision to deregulate shop closing laws. If deregulation is endogenously determined by economic and social conditions, the estimates of β_1 will be biased. Yet, as discussed in the previous section, the most important control state of Bavaria was assigned to the control group capriciously, implying that the deregulation experience at hand does not suffer from endogeneity problems. Further, it bears notice that endogeneity would result in upward-biased estimates, as new policies are likely to be implemented where the gain from a law change is greatest. Hence, given that I find negative deregulation effects on employment, my results are still valid in the presence of endogeneity, but would have to be interpreted as a lower bound on the absolute magnitude of employment losses.

As the analysis employs multiple time periods, inference based on the traditional treatment of standard errors can be misleading due to serial correlation (Bertrand et al., 2004). Furthermore, the employment outcomes vary at the district level, while the regressor of interest varies only at group level, which results in downward-biased standard errors (Moulton, 1986). To address these concerns, I follow the proposition by Angrist and Pischke (2009) and use Huber-White robust standard errors clustered at state level. This allows for an arbitrary autocorrelation process of the error terms within the states over the years, reducing the bias in the standard errors. In a recent study, Brewer et al. (2013) show that even if the number of clusters is relatively small, tests of the correct size can be obtained. In particular, this is achieved by computing a t-statistic with cluster robust standard errors that use residuals scaled by $\sqrt{\frac{G(N-1)}{(G-1)(N-K)}}\sqrt{G/(G-1)}$ and using critical values from a t-distribution with $G-1$ degrees of freedom. The robustness of the results is additionally confirmed by implementing the two-way bootstrap clustering method suggested by Cameron et al. (2008).

4.3.2 Data and Descriptive Evidence

The primary data source employed for the analysis is the Establishment History Panel (*Betriebshistorikpanel*, BHP) for the period from 2003 to 2010. The BHP is a 50 percent sample of all establishments in Germany with at least one employee liable to social security as of the 30th June of a given year, stratified by establishment size (for details, see Gruhl et al., (2012)). While the dataset contains information on regular employees and marginal employees, the self-employed and unpaid family members are not included. In addition to the number of total employees, employment information is available at a more disaggregated level, i.e. by gender, working time arrangement and education. The BHP further contains a 5-digit industry identifier, as well as information on the district in which an establishment is located.

To construct the sample, I first translate total employment into full-time equivalents (FTE) at the firm level.[6] Then, by aggregating the firm-level employment information at the level of 412 districts, I construct a panel with district-year observations. In order to enable analyses of effect heterogeneity, I additionally calculate district employment bifurcated by working-time (full-time vs. part-time), gender and establishment size. As the dataset does not include information on sales volume or floor size, stores are grouped according to their number of employees. I follow the classification of Viviano (2008) and define firms as small if they have up to five employees, as medium when there are more than five but less than sixteen employees, and as large when there are sixteen employees or more.

As discussed in section 4.3.1, the main dependent variable is the fraction of retail employment in overall employment. For the purpose of my analysis, it is reasonable to restrict the retail sector to the sale of new goods in stores (Sector Industry Code 521 to 524). Specifically, I exclude retail sale not in stores (SIC 526), which is not bound to opening restrictions, as well as sale of second-hand goods (SIC 525).[7]

In order to construct the time-varying district characteristics that are used as control variables, I match information on tourism, proxied by the number of overnight stays, as well as on disposable income in district d and year t. These time series are provided by the German Federal and State Statistical Offices. In the Establishment History Panel, districts are defined following a time-consistent definition of 412 administrative districts in West Germany according to the territorial status of 2008. To make the data from the Federal Statistical Offices consistent with this classification, six districts in Saxony-Anhalt have to be excluded from the analysis.[8]

Table 4.2 presents summary statistics on the variables employed in the analysis for the treatment and control districts in the baseline sample for the years 2003 and 2010. Columns 1 and 4 report the means for the control districts and columns 2 and 5 report those for the treatment districts in each year. Columns 3 and 6 include the respective differences and indicate the statistical significance from t-tests on the equality of means. The average fraction of district employment in retail amounts to 8.19% and 8.14% of the overall working population in the control and treatment states, respectively. This number also comprises those working in out-of-store retail environments (e.g. mail order business and markets) as well as employment in second hand stores. Without these categories, the retail employment share decreases to approximately 7.8%. Since part-time employees are overrepresented in the retail sector relative to the overall working-time structure, the retail employment share declines again when employment is expressed in full-time equivalents. Table 4.2

[6] The data lacks exact information on hours worked. In order to calculate FTE employment, I follow Dauth (2013) and weigh employment according to a worker's employment status: Employees are assigned a weight of 1 if they work full-time, a weight of $\frac{24}{39}$ if they work in major part-time (between 19 and 39 hours) and $\frac{16}{39}$ if they work in minor part-time (up to 19 hours).

[7] The industry classification changes in 2009. In order to obtain a consistent classification of the industry, I used the industry crosswalk provided by the Federal Statistical Office. Fortunately, this crosswalk allows a 1:1 mapping of the industries at the 3-digit level for industry code 521 to 524.

[8] Within the realm of several district reforms, county boundaries were redrawn in some East German states. In most cases, this does not pose a problem, because districts were merged together. Yet, in Saxony-Anhalt, boundaries were redrawn in a way such that some former districts cannot be matched 1:1 to new ones.

Table 4.2: Summary Statistics of Variables Employed for 2003 and 2010

	2003			2010		
	Control	Treatment	Diff.	Control	Treatment	Diff.
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variables						
Fraction in retail	8.19	8.14	.05	8.13	8.06	.07
	(.21)	(.12)	(.24)	(.22)	(.10)	(.22)
Fraction retail w/o 525 & 526	7.73	7.81	-.07	7.72	7.75	-.03
	(.18)	(.11)	(.22)	(.16)	(.10)	(.20)
Fraction in retail (FTE)	6.88	6.89	-.01	6.88	6.78	.10
	(.17)	(.11)	(.21)	(.16)	(.10)	(.19)
Fraction full-time	4.09	4.03	.06	3.74	3.55	.19
	(.12)	(.07)	(.14)	(.11)	(.06)	(.12)
Fraction part-time (FTE)	2.79	2.86	-.07	3.15	3.23	-.09
	(.04)	(.05)	(.09)	(.06)	(.05)	(.09)
Fraction in small estbl.	2.94	2.82	.12	2.80	2.69	.11
	(.07)	(.05)	(.99)	(.06)	(.04)	(.08)
Fraction in medium estbl.	1.02	1.04	-.02	1.08	1.03	.05
	(.03)	(.03)	(.05)	(.04)	(.02)	(.05)
Fraction in large estbl.	2.92	3.03	-.11	3.01	3.07	-.06
	(.17)	(.08)	(.18)	(.15)	(.08)	(.16)
Fraction female	4.71	4.75	-.04	4.78	4.71	.08
	(.12)	(.07)	(.14)	(.11)	(.01)	(.13)
Fraction male	2.18	2.15	.02	2.12	2.10	.01
	(.08)	(.05)	(.09)	(.07)	(.04)	(.08)
Control Variables						
Tourist stays (log)	12.82	13.01	-.19**	12.95	13.25	-.30***
	(.11)	(.06)	(.12)	(.10)	(.06)	(.11)
Disp. inc. PP (log)	9.78	9.69	.09***	9.92	9.83	.09***
	(.01)	(.01)	(.01)	(.10)	(.01)	(.01)
Working age pop.	88,490	149,361	-60,871***	88,446	114,952	-26,506***
	(9,007.32)	(9,726)	(17,736)	(9,516)	(144,982)	(17,733)
Population	132,203	221,904	-89,700***	132,904	329,985	-197,080***
	(12,785)	(13,872)	(25,284)	(13,751)	(14,209)	(26,011)

Notes: Number of observations: 412 for each year. Dependent variables are expressed as the fraction of FTE district employment. Standard deviations in parentheses. Sector 525 and 526 comprise out-of-store retail and second hand retail.

also displays employment shares disaggregated by establishment size and gender. Notably, when comparing treatment and control states, employment is similarly distributed within the respective groups.

In sum, an unconditional cross-sectional comparison of the dependent variables between the treatment and the control group reveals no significant differences in the structure of retail employment. Yet, it bears notice that the treatment districts have, on average, a larger population, receive more tourist stays and have a lower income level.

The validity of the diff-in-diff approach hinges critically on the assumption that in absence of treatment, employment in both groups would evolve identically. As a first descriptive test of the validity of this identifying assumption, I compare pre-deregulation trends in retail employment in the treatment and the control group. If retail employment has evolved similarly in both groups before the treatment, it is likely that any differences in the development after the treatment can be attributed solely to deregulation. Figure 4.1 depicts the average fraction

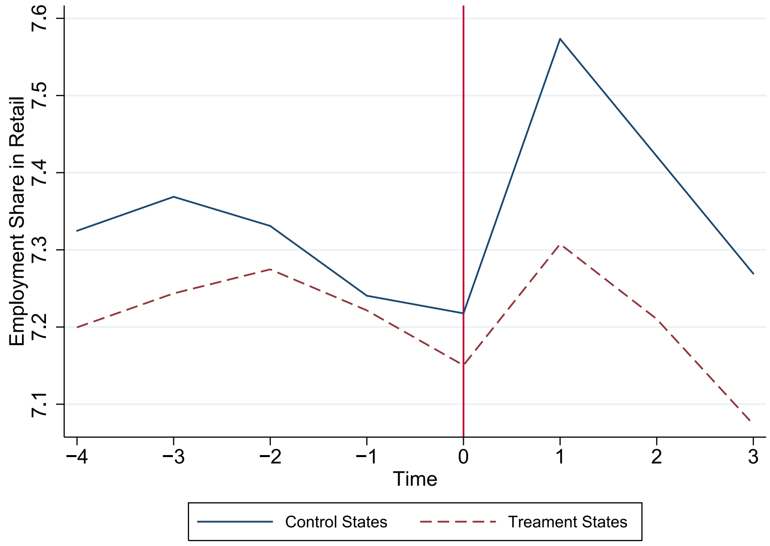


Figure 4.1: Employment Shares in Retail

Notes: Fraction of retail employment in overall employment in the treatment and control group between 2003 and 2010 using a relative time scale. Employment shares are calculated from the Establishment History Panel (BHP).

of retail employment in overall employment in the treatment and the control group between 2003 and 2010, using a relative time scale. Specifically, year zero is normalized to the first year in which the state laws were enacted.[9] The data reveal a parallel increase in employment shares at the beginning of the observation period, before retail employment decreases in both groups. In the first year after the deregulation of shop opening hours, marked by the vertical dashed line in the figure, employment shares in both groups decrease slightly and then exhibit a relatively sharp increase. One explanation for this increase is the economic crisis, during which employment in retail deteriorated relatively less that overall employment.[10] In the two subsequent years, the retail employment share declines again. Although only descriptive, the figure presents evidence for a similar trend of retail employment shares in both groups. Yet, it bears notice that also in the post-treatment period, employment developments do not differ markedly. The validity of the identifying assumption is further tested in section 4.4.2, where I perform several placebo experiments.

[9]Because for all but one of the federal states this was in 2007, year-zero employment in the control states also represents the year 2007.

[10]It bears notice that the results of the following analysis do not hinge on the choice of the *share* of retail employment as the main dependent variable. As shown in section 4.4.2, similar results are obtained when considering log retail employment.

4.4 Results

4.4.1 Overall Retail Employment

I start the econometric analysis by assessing the aggregate employment effect of deregulation. Table 4.3 shows the results for the regression of the log fraction of all workers employed in retail. The simplest specification reported in column 1 includes the deregulation dummy as well as year and district fixed effects, which are highly significant in most instances. Due to the large number of district fixed effects and time trends included, I only report the result on the variable of interest. The coefficient in column 1 is negative and statistically significant at the 5% level, suggesting that deregulation decreased employment in the retail sector.

In order to control for potentially confounding factors, I augment the model with additional covariates that might independently influence the development of employment in the retail sector. As discussed in section 4.3.2, six districts in Saxony-Anhalt have to be excluded once covariates are added to the model. To see whether the mere exclusion of these districts changes the result obtained so far, I repeat the regression with the restricted sample. As can be seen in column 2, the size of the coefficient decreases marginally and the standard error does not change. It is therefore reasonable to assume that any changes in the size or significance of the estimate on the deregulation dummy will stem from the inclusion of additional control variables rather than from the sample restriction itself.

Retail sector employment might be positively affected by tourists, as they create additional purchasing power in a region. I test this hypothesis by including the number of overnight stays of visiting foreigners in district d at time t. The positive, albeit insignificant, coefficient in column 3 supports this conjecture. However, the inclusion only marginally alters the point estimate on the coefficient of interest. In the next column, I additionally augment the regression by a measure of average disposable income per person in district d in time t. The coefficient on the deregulation variable remains stable and the results indicate that disposable income is positively associated to employment in retail, although the coefficient is statistically not different from zero.

In column 5, the model is augmented by a full set of district-specific linear time trends. The precision of the estimates is increased considerably, with the size of the standard error being more than halved. The absolute value of the coefficient decreases only slightly and becomes significant at the 1% level. Also the inclusion of quadratic trends (column 6) hardly alters the point estimate. The coefficient suggests that the share of retail employment decreased by 1.5% as a consequence of the reform. Evaluated at the pre-treatment sample mean for the fraction of FTE retail employment in overall employment (6.88%), the point estimate translates into an average loss of approximately .1 percentage points of overall employment or about 19,000 full-time equivalent jobs in the deregulating federal states.[11]

[11] Employment in the average treated district amounts to 60,762 FTE workers in the pre-liberalization period. A decrease of this population by .1 percentage points implies a reduction of 61 FTE jobs per district and adds up to 19,000 full-time equivalent jobs in the treated states.

Table 4.3: Employment Effect of Deregulation: Baseline Results

Dependent Variable: FTE Retail Empl. Share (log)	(1)	(2)	(3)	(4)	(5)	(6)
Deregulation	-.019**	-.018**	-.019**	-.019**	-.017***	-.015***
	(.008)	(.008)	(.008)	(.008)	(.003)	(.005)
Tourism	no	no	.040	.044	.009	.020
			(.040)	(.042)	(.022)	(.014)
Disposable Income	no	no	no	.085	.171	.133
				(.083)	(.124)	(.117)
District × time trends	no	no	no	no	yes	yes
District × time^2 trends	no	no	no	no	no	yes
R^2	.900	.900	.901	.901	.954	.968
N	3,296	3,248	3,248	3,248	3,248	3,248

Notes: All regressions include district and year fixed effects. The explanatory variable "Tourism" is proxied by the log number of overnight stays in time t in district d. Robust standard errors in parentheses are clustered at the federal state level. *Significant at 10%, ** at 5%, *** at 1%.

Hence, the point estimate of -1.5% is quantitatively small and implies, on average, a rather moderate adverse employment effect of deregulation.

4.4.2 Robustness Checks

In this section, I perform several robustness checks of the main result, that the deregulation of shop closing laws induced a statistically significant reduction of retail employment in Germany. The results of these checks are depicted in Table 4.4, where the baseline estimate for the aggregate deregulation effect from Table 4.3 is reproduced in row 1 for comparison. One caveat to the identification strategy applied in the analysis is that the negative employment effect observed in the deregulating states might be driven by policies other than the liberalization of shop closing laws, which indirectly affect retail employment. To test this hypothesis, I perform two "placebo experiments". First, I fit a model according to equation 1, where the dependent variable is the share of employment in the hotel sector, a service sector similar to retail trade (Bertrand and Kramarz, 2002). If the estimated coefficient for the hotel sector is negative, the differential development of retail employment in the treatment group would falsely be attributed to the deregulation. Instead, such a result would be suggestive of other state policies that exert an adverse effect on overall employment. Row 2 reports estimates for the hotel sector. The coefficients are positive and do not differ significantly from zero in the fully specified model, confirming that the results obtained in Table 4.3 are indeed specific to the retail sector.

As a second test, I prepone the timing of the liberalization by two years. Here, a coefficient significantly different from zero would indicate that the evolution of retail employment has evolved differently in the treatment and the control groups, but due to some other reason than the treatment. The placebo experiment is presented in row 3 and reveals that the estimated

Table 4.4: Robustness Checks

	(1)	(2)	(3)
1. Baseline estimates from Table 4.3	-.019**	-.017***	-.015***
	(.008)	(.003)	(.005)
2. Placebo: Estimates for the hotel sector	.038	.028*	.026
	(.025)	(.010)	(.018)
3. Placebo: Pre-ponement of timing	-.004	.020	.016
	(.005)	(.012)	(.012)
4. Treatment intensity	-.015	-.021**	-.018*
	(.019)	(.008)	(.009)
5. Log employment	-.036***	-.013**	-.015***
	(.011)	(.005)	(.005)
6. Retail as a fraction of working age population	-.026***	-.011**	-.014***
	(.008)	(.004)	(.004)
7. Weight by district population	-.002	-.015***	-.014**
	(.007)	(.004)	(.006)
8. Bootstrapped Standard Errors	-.019	-.017*	-.016**
	[.55]	[.070]	[.043]
Add. Controls	yes	yes	yes
District $\times$ time trends	no	yes	yes
District $\times$ time^2 trends	no	no	yes

Notes: N=3,248. Each cell reports the coefficient on the treatment variable for one regression. All regressions include district and year fixed effects. If not reported differently, standard errors in parentheses are clustered at the federal state level. p-values in brackets. * Significant at 10%, ** at 5%, *** at 1%.

policy effect is not different from zero.

I next consider the robustness with respect to an alternative definition of the treatment variable. So far, the treatment was reflected by a dummy variable which indicated whether a federal state had deregulated its shop closing laws or not. However, as discussed in section 4.2, there also exists variation in the scope of deregulation between the states. To incorporate this additional variation, I estimate a model where the explanatory variable is a measure of deregulation intensity. Specifically, the variable reflects the percentage change in hours that shops are allowed to open under new state legislation. The treatment intensity takes values between zero (for non-deregulating states) and 0.72 for the states with the most liberal regulations (see Table 4.1). The coefficient estimates reported in row 4 are consistent with the baseline result.

So far, the retail employment variables used in my analysis were expressed as fractions of overall employment. Hence, also changes in the overall working population influence the dependent variable. Further, employment evolutions in retail influence both the nominator and the denominator. To address this potential concern, I re-estimate the model and express retail employment in levels instead of shares and as the fraction of the overall working age population, respectively. For the level of retail employment (row 5), the result is identical to the baseline estimate in the fully specified model. The coefficient for retail employment as the fraction of the working age population (row 6) is marginally smaller than the baseline but remains highly significant. In row 7, I present results where observations are weighted by the respective district population in order to account for differences in the district size and to make the results representative for the average German employee. Reassuringly, the estimated coefficient is only slightly smaller than the baseline estimate. Finally, in row 8, I confirm the validity of the results by implementing the two-way bootstrap clustering method suggested by Cameron et al. (2008).

I further test the robustness of my results by analyzing whether they are driven by a certain year or a specific federal state. To this end, I re-estimate the model, and consecutively exclude one year or state from the regression. The results from these estimations are depicted in Appendix Tables 6.3 and 6.4. As can be seen, they prove robust to the exclusion of particular years or federal states.

4.4.3 Effect Heterogeneity by Establishment Size

This section is devoted to the analysis of effect heterogeneity with respect to store size. As discussed in the introduction, the mechanism through which deregulation may affect the distribution of employment among small and large shops bases on productivity differences between establishments of different size. Specifically, these may result from economies of scale, better organizational structure and more buyer power of large establishments (Haskel and Sadun, 2012). In the presence of such productivity differences, small retailers are not able to match longer shopping hours and eventually suffer from deregulation.[12] Figure 6.3 in the Appendix presents some descriptive evidence on the relationship between store size and productivity in the German retail sector. It displays average sales productivity for establishments of different size in the year 2005, where establishments are categorized by yearly sales and overall employees, respectively. As can be seen, sales productivity increases with establishment size. In shops with sales exceeding 10 million Euro, average sales per employee are almost three times larger than in shops with a sales volume of up to one million Euro.

To analyze whether deregulation has had an impact on the structure of the retailing sector, I re-estimate the model described by equation 4.1 separately for small, medium and large establishments. The results of these estimations are presented in Panel A of Table 4.5. In line with the theoretical predictions, deregulation has heterogeneous effects on stores of

[12] As the BHP does not contain information on actual opening hours, we cannot inspect the issue of heterogeneous opening hours extension. Yet, evidence from an earlier reform of the shop closing legislation in 1996 suggests that, indeed, size is an important determinant of whether stores actually use the leeway of extending opening hours beyond the existing level (Täger et al., 2000).

Table 4.5: Deregulation Effects: Results by Establishment Size

	Panel A: Dep. Var.: Empl. Share (log)			Panel B: Dep. Var: Number of Shops (log)		
	(1)	(2)	(3)	(1)	(2)	(3)
	Small Establishments ($\leq$ 5 empl.)					
Deregulation	-.014**	-.011*	-.013**	-.030***	-.016**	-.017**
	(.007)	(.006)	(.005)	(.008)	(.007)	(.007)
R^2	.962	.976	.981	.994	.997	.998
	Medium Establishments (6 to 15 empl.)					
Deregulation	.018	-.008	-.006	.008	-.004	-.004
	(.012)	(.008)	(.009)	(.012)	(.011)	(.011)
R^2	.886	.927	.938	.957	.970	.974
	Large Establishments ($\geq$ 16 empl.)					
Deregulation	-.025***	-.005	-.006	-.028***	.004	-.002
	(.007)	(.005)	(.005)	(.008)	(.011)	(.012)
R^2	.958	.973	.977	.969	.980	.983
Add. Controls	yes	yes	yes	yes	yes	yes
District $\times$ time trends	no	yes	yes	no	yes	yes
District $\times$ time^2 trends	no	no	yes	no	no	yes

Notes: N=3,248. Each cell reports the coefficient on the treatment variable for one regression. All regressions include district and year fixed effects. Standard errors in parentheses are clustered at the federal state level. * Significant at 10%, ** at 5%, *** at 1%.

different sizes. In particular, liberalization has led to a significant decrease of employment in small retail stores. The negative coefficient suggests that the share of employment in these establishments has decreased by 1.3%. Notably, employment losses have been accompanied by a significant decrease in the overall number of small shops (see top part of Panel B). In contrast, neither employment in medium and large establishments nor the number of these shops has been significantly affected by deregulation.

In sum, my results imply that deregulation has led to modest employment losses in the retail sector, which originate from employment decreases in small shops. One interpretation of the results is that the formerly regulated retail environment has facilitated the emergence of inefficient retailing structures with relatively low productivity and overstaffed operating levels. After deregulation, these less efficient formats disappear. This, in turn, results in a net decrease in employment, as the losses are not sufficiently compensated by employment creation in large establishments.

4.4.4 Further Employment Outcomes

In this section I analyze whether employment losses were concentrated among particular subsets of employees in the retail sector. To do so, I break down overall retail employment into different subsamples bifurcated by working time arrangement and gender and estimate the basic empirical model described by equation 4.1. The results are presented in Table 4.6, where each coefficient corresponds to a separate regression.

I start by analyzing whether deregulation has differentially affected full-time and part-time employment. The results show that the adverse effect of deregulation is exclusively borne by full-time employees. The estimated coefficient is highly significant and suggests that full-time employment has decreased by 2.5%. Evaluated at the average fraction of full-time employment in retail (3.92%), the point estimate suggests that full-time employment has decreased by .1 percentage points of the working population, which is equivalent to the aggregate effect. In contrast, the point estimates for part-time employment are close to zero and statistically insignificant.

Table 4.6: Deregulation Effects: Results by Employment Subset

	(1)	(2)	(3)
By working time arrangement			
Full-time employment	-.037***	-.029***	-.025**
	(.010)	(.006)	(.009)
Part-time employment	.002	-.006	-.003
	(.007)	(.005)	(.005)
By gender			
Female employees	-.024***	-.012***	-.010**
	(.008)	(.003)	(.004)
Male employees	-.015	-.032***	-.029***
	(.010)	(.007)	(.010)
Total employment (log)	-.017*	.004	-.000
	(.005)	(.003)	(.002)
Add. Controls	yes	yes	yes
District $\times$ time trends	no	yes	yes
District $\times$ time^2 trends	no	no	yes

Notes: N=3,248. Each cell reports the coefficient on the treatment variable for one regression. All regressions include district and year fixed effects. Standard errors in parentheses are clustered at the federal state level. * Significant at 10%, ** at 5%, *** at 1%.

In rows 3 and 4 I focus on the employment outcomes of male and female retail workers. While the coefficients for both genders are negative and statistically significant, it is worth noting that the point estimate for male employees is almost three times larger than its counterpart for the female subsample. Finally, I estimate the deregulation effect on overall district employment. This is to address the question whether the effect on employment in the retail sector represents a redistribution across sectors or whether overall district employment declined as a result of deregulation. The point estimate in column 1 of row 5 is negative and statistically significant at the 10% level, implying a decrease of overall employment by approximately .2 percent. Yet, once time trends are added to the model (column 2 and 3), the magnitude of the estimated coefficient decreases substantially and becomes statistically insignificant.

4.5 Sales and Prices

To put the employment results into a broader context, it is interesting to analyze whether the deregulation of shop closing laws has also affected sales and prices in the retail sector. Unfortunately, the study of sales and prices is subject to some data limitations, as neither sales data nor data on consumer price indices exist at the district level in Germany. However, I was able to collect monthly sales and price data at the federal state level from the Regional Statistical Offices between 2006 and 2008 and 2005 and 2010, respectively.[13]

I start by analyzing the deregulation effect on sales in the retail sector. From a theoretical perspective, the sales effect of deregulation is ambiguous. Stützel (1978) argues that changes in opening hours will not have first order effects on the demand for final goods, as consumers would respond to longer opening hours by making the same purchases in a longer time interval. In contrast, Gradus (1996) and Burda and Weil (2005) develop theoretical frameworks, where "Stützel's Paradox" does not hold in general, but where positive sales effects are possible. To analyze the deregulation effect on sales, I fit the following model:

$$Y_{st} = \alpha + \beta_1 Dereg_{st} + \mathbf{X'_{st}}\beta_2 + \gamma_t + \delta_s + \varepsilon_{st}. \tag{4.2}$$

The dependent variable reflects nominal or real retail sales in state s in time t, where revenues are normalized to the reference year 2005. The regression includes state and time fixed effects as well as the same control variables that were used in earlier specifications, aggregated at the state level. The results are presented in Panel A of Table 4.7. For both nominal and real sales, the coefficient on the deregulation dummy is positive in the fully specified model in column 3, implying that revenue increased after deregulation. Yet, in quantitative terms, the estimated effect is relatively moderate, suggesting revenue gains of .5 to .8 percent. Additionally, the standard errors are large, rendering the coefficients not statistically different from zero.

The results obtained so far suggest that deregulation has not led to an increase in retail sales volume. Yet, another possible explanation for these findings is that deregulation may simultaneously affect retail sales and prices. In that case, the CPI based on all consumer goods, which is used to deflate the nominal sales data, is an imperfect indicator for price changes in the retail sector, resulting in an imprecise estimation of the sales effect.

To assess this possibility, I estimate the price effect of deregulation using CPI data from the Regional Statistical Offices. As consumer prices indices do not exist at the industry level but for different categories of goods, I obtain exemplary consumer price indices for food,

[13] See data Appendix for a detailed description of the sales and price databases.

Table 4.7: Deregulation Effects on Sales and Prices

	(1)	(2)	(3)
		Panel A: Sales	
Real Sales	-1.650	.190	.787
	(2.843)	(2.088)	(1.354)
Nominal Sales	-2.224	-.112	.489
	(2.771)	(1.964)	(1.212)
		Panel B: Prices	
Food prices	.080	-.432	-.331
	(.334)	(.457)	(.292)
Apparel prices	2.929	-1.306	-.528
	(1.904)	(.968)	(.512)
Furniture prices	.842	.217	-.196
	(.488)	(.222)	(.266)
Add. Controls	yes	yes	yes
District $\times$ time trends	no	yes	yes
District $\times$ time^2 trends	no	no	yes

Notes: N=576 in Panel A, N=1008 in Panel B. Each cell reports the coefficient on the treatment variable for one regression. All regressions include state and month*year fixed effects. Standard errors in parentheses are clustered at the federal state level. * Significant at 10%, ** at 5%, *** at 1%.

apparel and furniture as well as the overall CPI at the level of federal states. I normalize the CPI of the three product groups by the CPI for all consumer goods to fit models as described by equation 4.2. The results from this analysis are presented in Panel B of Table 4.7. For all product groups, the coefficients are negative, suggesting that relative prices in the retail sector have decreased after deregulation. This implies that sales volume may indeed have been positively affected by deregulation, which remained unidentified in the upper part of Table 4.7 due to retail specific price decreases. Yet, the coefficients are imprecisely estimated. Unfortunately, neither the sales nor the price data could be split further into subsamples to analyze effect heterogeneity by establishment size.

4.6 Conclusion

This paper presents empirical evidence that product market regulation affects labor market outcomes. The case studied is the deregulation of shop closing laws, introduced in Germany in 2006 and 2007. This reform conferred the legislative power regarding shop opening issues upon the federal states. I exploit regional variation in trading provisions to identify the effect of deregulation on employment outcomes and present evidence that the reform led to modest employment losses in the retail sector. In line with theoretical predictions, I show that these losses are concentrated among small retail establishments, while medium and large size establishments were unaffected by the law change. Further, I show that the decreases in employment were mainly borne by full-time employees and over-proportionally by male workers.

The key finding of an adverse employment effect stands in contrast to the main body of the existing - largely US-based - empirical literature, in which the majority of studies find that shop closing deregulation leads to significant employment gains. One may explain this discrepancy by a relatively high level of X-inefficiencies in the German retail sector prior to deregulation, associated with low productivity and excessive employment levels. Further reasons for the different findings involve high labor costs in Germany, which have the potential to suppress positive labor demand effects. Hence, my results suggest that in any debate on the employment consequences of deregulation, it is crucial to account for the conditions of the specific case at hand, as the post-liberalization path may vary considerably among sectors and countries (Blanchard, 2006; Boeri et al., 2006).

5 Public Sector Employment and Local Multipliers

5.1 Introduction

There is substantial variation in unemployment rates across regions in many European countries.[1] In order to equalize spatial dispersion, some policy makers consider the creation and relocation of public sector employment (Alesina et al., 2001; Smith, 2010). Using data for 412 German administrative districts, this analysis studies labor market adjustments in the private sector to public employment growth. It contributes to the existing literature by providing novel evidence on the impact of public sector growth on private sector employment in Germany. Further, it assesses how local wages respond to changes in public employment. To my knowledge, this aspect has remained largely unstudied in the empirical literature so far.

To analyze if and to what extent public employment creation has spillover effects on the private sector in Germany, I relate changes in private sector employment outcomes between 2003 and 2007 across German districts to an increase in the number of jobs in the public sector, allowing for price adjustments and endogenous factor reallocation. Because public sector employment growth may be endogenous and ordinary least squares estimates would be confounded, I construct a shift-share instrument following Bartik (1991) that uses initial local shares and national growth of public sector employment to isolate exogenous labor demand shocks in the public sector. The results of this analysis suggest that public employment has substantial crowding out effects on employment in the private sector. More specifically, I estimate that 100 additional public jobs crowd out 74 jobs in the private sector. I further show that public sector employment increases local wages and thereby affects the industry mix in the private sector: On the one hand, an increase in wages leads to a deterioration of the competitiveness of the tradable goods sector and employment in this sector decreases. On the other hand, employment in the nontradable industries remains largely unaffected because increases in wages and prices are offset by rising local demand for nontradable goods.

The findings of the present study are informative for local policies that intend to stimulate employment by creating jobs in the public sector because, from a theoretical point of view, the overall effect of public sector employment growth on employment in the private sector

[1] For example, in Germany, the regional unemployment rate in Berlin in 2013 amounted to 12.7% and is three times larger than in Bavaria (3.8%).

is ambiguous: Public employment programs create direct employment and have positive spillover effects on employment in the private sector if they raise aggregate demand. However, this positive effect on employment may be offset by increasing wage pressure and rising taxes (Algan et al., 2002). What is more, if the public sector produces goods and services that are substitutable to these provided by the private economy, employment in the private sector will be harmed.

My analysis combines studies on the impact of public sector employment with a growing literature on local multipliers and spillover effects. A number of cross-country analyses has explored the impact of public sector employment on labor market outcomes. While the majority of these studies find that public sector employment crowds out employment in the private sector, the magnitude of the effects varies substantially between different studies. Using data on 22 OECD countries, Edin and Holmlund (1997) show that an increase in public sector employment reduces unemployment in the short run but has no significant effect in the long run. Boeri et al. (2000) focus on short-run effects of public employment on the private sector and estimate that 10 additional public jobs destroy 3 jobs in the private economy. Algan et al. (2002) analyze a panel of 17 OECD countries between 1960 and 2000 and find that in the long run, 10 public sector jobs crowd out 15 private jobs. The problem with these studies is that individual countries often differ strongly with respect to their institutional frameworks, which are likely to influence employment outcomes and are very difficult to control for. In addition, only few of the studies account for endogeneity and reverse causality issues. In this analysis, I circumvent the problem of different institutional frameworks as the analysis is conducted at the level of local labor markets. Additionally, I use an instrumental variable technique that isolates exogenous shocks to labor demand in the public sector.

Existing literature on local multipliers has so far mainly focused on spillover effects from the tradable sector on employment outcomes in the nontradable sector. Moretti (2010) presents evidence for strong positive spillover effects in the United States, estimating that each additional job in the manufacturing sector creates 1.6 jobs in nontradable industries. Moretti and Thulin (2013) perform a similar analysis for the Swedish labor market and conclude that local multiplier effects are substantially smaller in Sweden. In addition, the authors show that local multipliers vary considerably across industries. In a similar vein, Humphreys and Marchand (2013) examine the spillover effects of the opening of casinos in Canada. They find that each job in the gambling industry creates one or two jobs in the hospitality industry. In contrast to studies of multiplier effects of the manufacturing industry, literature on local spillover effects of public sector employment is scarce. One notable exception is a recent study by Faggio and Overman (2014) who analyze the impact of public sector employment on private sector employment for the UK at the Local Authority level. The authors find no aggregate effects on private employment in the short-run, but show that public sector employment differentially affects tradable and nontradable private sector employment. When considering longer time periods, they find crowding out effects that are close to unity. An analysis of the effects of public sector employment for Germany and its comparison with existing estimates for the UK is interesting because, as will be discussed later, the magnitude of the employment effects depends crucially on the labor supply elasticity, which is likely to differ across both countries. For example, Germany has a more generous benefit system and exhibits lower labor mobility. Because these features determine the labor supply elasticity, the effects of public sector employment on the private sector may also vary.

Finally, this study is also related to the literature on pay structures in the private and public sectors. A cross-country analysis across numerous EU countries conducted by de Castro et al. (2013) point to the existence of a significant public-private pay gap in the majority of countries studied. The authors estimate that in Germany, earnings in the public sector are about 10% higher than wages in the private sector. This gap is found to be larger for females than for males. Studies by Dustmann and van Soest (1997; 1998) provide evidence that wages in Germany, conditional on personal characteristics, are higher in the public sector for women, but higher in the private sector for men. Melly (2005) uses quantile based approaches to show that, for both genders, the pay gap is positive and large for workers at the bottom of the wage distribution and decreases with wages. In addition, wages in the public sector are found to be less dispersed (Jürges, 2002).

The remainder of the chapter is structured as follows. In the next section I present the logical underpinning of the local multiplier effect of public sector employment on private sector employment. I will then derive a number of hypotheses and describe the empirical approach to test these. Section 5.3 gives an overview of the datasets that are used in the econometric analysis and provides some descriptive evidence. The empirical analysis is conducted in section 5.4. Section 5.5 concludes.

5.2 Conceptual Framework and Empirical Strategy

5.2.1 Conceptual Framework and Empirical Predictions

Here I follow Faggio and Overman (2014) who augment the theoretical considerations of Moretti (2010; 2011) concerning the impact of tradable private sector employment on nontradable industries by taking into account the direct and indirect effects of public employment creation on employment and wages in the private sector. Consider a closed economy with spatially separated regions where labor is perfectly mobile across sectors within regions. Furthermore, assume the existence of a positive public-private sector pay gap. Hence, when jobs are created in the public sector, a region's aggregate income and employment level increase. This, one the one hand, raises local demand for nontradable services (e.g restaurants, retail). On the other hand, the public sector may provide goods that are substitutes for private sector provision (e.g. private schools, hospitals or postal services). Unless this substitution effect dominates the income effect, employment in the nontradable sector will increase. The magnitude of this multiplier effect depends on consumer preferences for nontradables, technologies in the nontradable sector, and on offsetting general equilibrium effects on wages and prices. That is, the more elastic is labor supply, the smaller will be regional wage increases and the larger will be the multiplier effect on the nontradable sector. Labor supply elasticity, in turn, is determined by exogenous factors such as labor mobility and the generosity of the benefit system.

Assume further that local demand is a negligible component of total demand for tradable goods. Then, the local increase in wages hurts employment in tradable industries. The reason is that the increase in production costs decreases the competitiveness of tradable industries, while positive demand effects resulting from an increase in local income are absent. Increases in local prices of nontradables and housing will further decrease employment in the tradable sector.

This conceptual framework provides a number of empirically testable implications. Firstly, the model predicts that an increase in local labor demand for public employment will cause a change in the structure of employment away from the tradable sector towards the nontradable and the public sector. Secondly, the relative magnitudes of the two countervailing effects in the tradable and the nontradable sector determine whether the overall spillover effect from public to private sector employment is positive or negative. Finally, an increase in public sector employment should lead to an increase in private sector wages as well as to rising prices of nontradables.

5.2.2 Empirical Strategy

Econometric Specification

In order to test the empirical implications of the conceptual framework for Germany, I conduct an empirical analysis at the level of local labor markets. I start by assessing whether public sector employment has effects on overall private sector employment and on other labor market outcomes, such as unemployment, the local labor force and migration. Then, I investigate whether these effects are heterogeneous across different industries and explore whether public employment increases local wages. For the analysis of employment outcomes, the following empirical model is estimated:

$$\Delta L_r = \alpha + \beta \Delta PSC_r + \gamma X_r + \varepsilon_r. \tag{5.1}$$

The explanatory variable, ΔPSC_r, represents the regional contribution of public sector employment to overall employment and is defined as

$$\Delta PSC_r = \frac{E^{pub}_{r,2007} - E^{pub}_{r,2003}}{E^{tot}_{r,2003}} \tag{5.2}$$

In this expression, public sector contribution is measured as the change in public sector employment, E_r^{pub}, between 2003 and 2007 in region r, normalized by overall regional employment in the year 2003, $E_{r,2003}^{tot}$. This estimation approach is similar to Card (2007) and Faggio and Overman (2014), where total employment growth is decomposed into the sum of the contributions from the private and the public sector, respectively. Similarly to the main explanatory variable, the dependent variable, ΔL_r, represents the change in private sector employment in district r between 2003 and 2007, normalized by total initial district employment. The parameter of interest, β, is the coefficient on the contribution of public sector employment to overall employment growth. If $\beta > 0$, public sector employment has multiplying effects on the private sector, whereas a $\beta < 0$ would imply that public sector employment crowds out employment in the private sector. In additional specifications, I split private sector employment into the tradable and the nontradable sector to capture potentially heterogeneous effects. I further employ the empirical model described by equation 5.1 to estimate the effect of public sector employment on unemployment, the size of the local labor force and migration. For ease of comparison, these variables are also normalized by total initial district employment.

To control for potentially confounding factors, the model is augmented by start-of-period district characteristics, X_r. These controls include the regional qualification structure, as a number of studies find strong correlation between educational composition and employment growth (Glaeser and Resseger, 2010; Südekum, 2010). I also add total initial district population (Südekum, 2008). In the final specification, the model is further augmented by a dummy indicating whether a district is located in the former Eastern part of Germany and a variable that groups the districts into two basic area types (districts in urban and rural areas), using a classification developed by Lehmer and Möller (2010) for their analysis of the urban wage premium.

For the analysis of the wage outcomes that vary at the individual level, I pool microdata on log real daily wages from 2003 and 2007 to estimate wage equations of the following form:

$$\ln W_{irt} = \alpha + \beta \left(\Delta PSC_r \times \mathbb{I}\left[t = 2007\right]\right) + \gamma X_{irt} + \varepsilon_{irt}, \tag{5.3}$$

where the subscript i denotes individual observations. The term $\left(\Delta PSC_r \times \mathbb{I}\left[t = 2007\right]\right)$ interacts public sector contribution with a dummy for the year 2007. Thus, the coefficient on this expression measures the impact of public sector contribution on wage growth during 2003-2007. The model is augmented with a set of worker level covariates, X_{irt}, each interacted with time dummies. The vector of individual controls includes a quartic in age and dummies for foreign citizenship, gender, two part-time indicators as well as dummies for seven broad occupational groups and 13 broad industry categories. Because the explanatory variable varies at the level of districts, while wages vary at the individual level, I use Huber-White robust standard errors clustered at the district level (Moulton, 1986).

Identification and Instrumental Variables Approach

One concern for the estimation of equation 5.1 is that public sector growth may be correlated with unobserved determinants that also influence employment growth in the private sector. In this case, the OLS estimator of the model described by equation 5.1 would be inconsistent and biased for β. In principle, this bias can be either negative or positive. If, for example, local governments attempt to offset negative shocks to private sector employment by creating jobs in the public sector, the correlation between public sector employment and the error term is negative and the estimate of β will be downward-biased. In contrast, if public employment responds to overall population growth, estimates of β will suffer from upward-bias. Hence, to identify the *causal* effect of public employment growth on private sector employment, I employ an instrumental variable approach that isolates exogenous variation in the demand for public sector employment following Bartik (1991).[2] The instrument is represented by a weighted average of national changes in public sector employment between 2003 and 2007, with weights reflecting the district specific public employment share in region r in the base year 2003. To address the issue that district changes in public sector employment drive nationwide developments, national changes are computed excluding region r:

$$\frac{E^{pub}_{2003}}{E^{tot}_{2003}} \times \frac{E^{pub}_{-r,2007} - E^{pub}_{-r,2003}}{E^{tot}_{-r,2003}} \tag{5.4}$$

This expression differs from the expression in equation 5.2 because it employs *nationwide* public sector employment growth and thereby abstracts from region-specific labor demand shocks that may induce bias. Instead, it reflects the assumption that in the absence of regional shocks, each district would have changed its public sector employment by an equal share. These nationwide changes affect regions differently due to their public-private sector mix in the base year 2003. Then, for example, if national public sector employment growth is positive, the district that initially exhibits a higher share of public sector employment experiences a larger increase in the demand for public jobs.

Because the expression described by equation 5.4 does not reflect local economic conditions, it is arguably orthogonal to the error term and therefore provides an appealing instrument for ΔPSC_r. Figure 5.1 sketches the estimation strategy by plotting public sector contribution against the instrument described by equation 5.4, which is equivalent to the first-stage regression without additional controls. The figure shows that the predictive power of the instrument is substantial and highly significant, with a coefficient of 2.34 and a t-ratio of above 11.

[2]Similar applications can be found in Card (2007), Moretti (2010) and Faggio and Overman (2014).

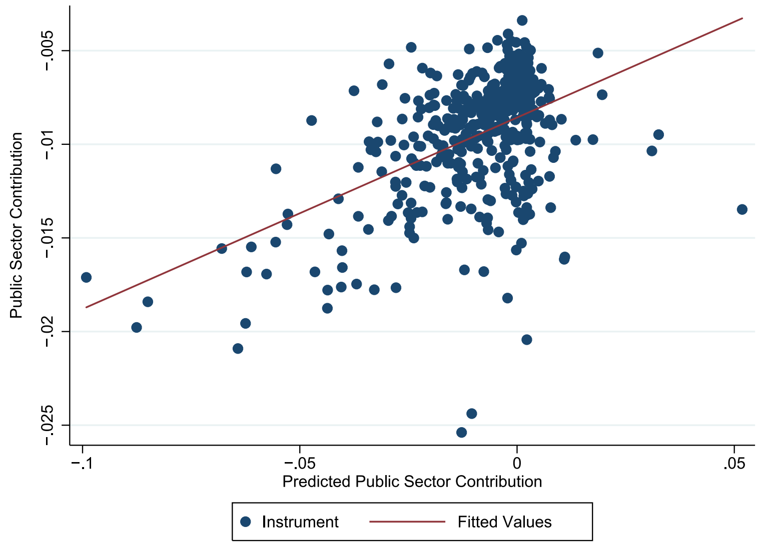


Figure 5.1: First Stage Regression

Notes: Figure plots the instrument against regional public sector contribution for 402 districts. The line corresponds to the predicted public sector contribution, where the slope is 2.34 and the t-value is 11.12.

5.3 Data Description

I consider employment and wage outcomes for 412 districts in Germany for the years 2003 and 2007. Information on public and private sector employment is derived from the German Federal and State Statistical Offices. Within its work force statistics (*Personalstandsstatistik*), the German Federal Statistical Office provides yearly information on overall personnel employed in the public sector as of the 30th of June at the district level. As this dataset covers the full universe of public employees, it can be considered as highly reliable. The data covers all workers employed in the public sector, including the central government, state and local authorities and financial and non-financial public enterprises. The data also comprises both types of public employees, i.e. civil servants and blue-collar or white-collar employees. The Federal Statistical Office further provides information on overall employment at the district level. This information covers employees subject to social security contributions, self-employed, marginally employed as well as employees in the public sector. Hence, private sector employment can be calculated by subtracting public employment from total employment in each region and year. Because of missing data in the public employment statistics, I am forced to exclude ten districts. Thus, the final sample comprises 402 districts, of which 322 are located in the Western and the remaining 80 in the former Eastern part of Germany.

The information on the variables that are used as regional controls are also obtained from the Federal and Regional Statistical Offices. Table 5.1 presents summary statistics for the main variables employed in the analysis. In 2003, the share of public employment in overall employment amounted to 11 percent. Between 2003 and 2007, overall employment grew, on average, by 2 percent. As shown by the contributions of public and private sector, which amount to -1% and 3%, respectively, this overall growth results from countervailing developments in the public and the private sector. The standard deviations of these variables are large, indicating that there is substantial variation in sectoral employment changes across German districts.

Table 5.1: Summary Statistics

	Workforce Statistics		SIAB data	
	Mean	Std. Deviation	Mean	Std. Deviation
Dependent Variables				
Total employment 2003	93,649	121,668	1,142	1,442
Total employment growth 2003-2007	.02	.03	.01	.044
Private sector employment 2003	83,948	108,490	893	1,140
Private sector share 2003	.89	.04	.78	.04
Contribution private 2003-2007	.03	.03	.02	.04
Tradable sector employment 2003	-	-	660	881
Non-tradable sector employment 2003	-	-	233	274
Contribution tradable 2003-2007	-	-	.02	.04
Contribution nontradable 2003-2007	-	-	.00	.02
Public sector employment 2003	9,701	13,977	-	-
Public sector share 2003	0.11	.04	-	-
Contribution public 2003-2007	-.01	.02	-	-
Δ Unemployment 2003-2007	-.02	.02	-	-
Δ Labor Force 2003-2007	-.02	.02	-	-
Control Variables				
No degree 2003	0.19	.05	-	-
Vocational degree 2003	0.73	.05	-	-
University degree 2003	0.08	.04	-	-
Population 2003	198,755	226,310	-	-

Notes: N=402. Changes in unemployment and the labor force are normalized by total employment in 2003. Education variables are expressed as the local share of employees with the relevant education qualification.

In part of the analysis, I split private sector employment between tradable and nontradable industries. Because the work force statistics from the Federal Statistical Offices that are used to classify employment into the public and the private sector do not provide information on detailed industries at the regional level, I use the Sample of Integrated Labor Market Biographies (SIAB) to obtain a division into tradables and nontradables. The SIAB is a two percent random sample drawn from the full population of the Integrated Employment Biographies provided by the Institute of Employment Research (for details, see Dorner et al. (2010)). This dataset contains employment information on individuals subject to social security contributions and on the marginally employed. It includes information on occupation and workplace location at the district level and detailed industry codes down to the 5-digit SIC level, as well as on daily wages. To obtain regional employment measures, individual employment spells are aggregated at the district level, where each spell is weighted by its respective length.

The SIAB does not contain a measure of public sector employment. To restrict the sample to private sector employment, I therefore first exclude three sectors which are typically considered as public: SIC75 (public administration and defense), SIC80 (education), and SIC85 (health and social work). Although the majority of the services provided by these sectors is likely to be provided publicly, one has to bear in mind that this sample restriction certainly also leads to the exclusion of some workers employed in the private sector (e.g. private school teachers). Further, I follow Faggio and Overman (2014) and exclude mining and quarrying (SIC10-SIC14), electricity, gas and water supply (SIC40-SIC41), transport and communication (SIC60-SIC64), as well as extraterritorial organizations and bodies (SIC90-SIC95). These sectors are excluded because they provide public goods or are heavily regulated, or a non-negligible share of employment in these industries is public. The definition of tradable and nontradable industries follows Dustmann et al. (2014), who classify sectors based on the geographical range of their markets. More specifically, they define industries with export volumes below the 25th percentile of the distribution of export volumes in 1995 as nontradables and sectors above this threshold as tradable sectors.[3] Table 5.1 also presents summary statistics for the SIAB data. Here, 78% of 2003 employment is classified as private. The share is smaller than in the data from the Federal Statistical Office, which is likely to result from the sectoral classification of the private-public employment split. The positive private sector contribution, which is slightly smaller in the SIAB data, results entirely from employment increases in the tradable sector.

The wage variable is real gross daily wages, which are also obtained from the SIAB. As wages in this dataset are top-coded at the social security contribution threshold, I impute right-censored wages using an imputation algorithm by Gartner (2005). Wages are deflated by the national Consumer Price Index (base year: 2005), which does not account for local price levels.

5.4 Results

5.4.1 The Impact of Public Sector Employment on Private Sector Employment

I start the empirical analysis by exploring the relationship between public sector employment growth and employment growth in the private sector. To do so, I estimate equation 5.1, where the dependent variable is the contribution of private sector growth to overall employment growth between 2003 and 2007. The OLS results are presented in the upper panel of Table 5.2. In the first column, the only explanatory variable is public sector contribution. The estimated coefficient is negative and statistically highly significant, implying that public sector employment crowds out employment in the private sector. The point estimate of -.522 is economically large and suggests that ten additional jobs in the public sector crowd out

[3] I thank Alexandra Spitz-Oener for making the classification available to me.

approximately 5 jobs in the private sector.

In the remaining columns of Table 5.2, the bivariate model is augmented with a set of additional explanatory variables which might independently affect private sector employment growth. In column 2, I control for total start-of-period population in a district. The coefficient on total initial population is negative but insignificant and leaves the magnitude and significance of β unchanged. Column 3 augments the regression model with the shares of employees that are medium-skilled and high-skilled, with the share of low-skilled workers being the reference category. These controls modestly increase the estimated negative crowding out effect of public sector employment. Finally, in column 4, I include a dummy variable that indicates whether a district is located in the former Western part of Germany as well as information on districts' area type. Unsurprisingly, private sector contribution is larger in the Western part of Germany, while the coefficient on the urban area dummy is small in size and statistically insignificant. Notably, the inclusion of the additional explanatory variables leaves the significant, negative relationship between public sector employment growth and the growth of private sector employment largely unaffected. When all control variables are simultaneously included (column 5), the point estimate of -.574 implies that the creation of ten jobs in the public sector crowd out approximately six jobs in the private sector.

As discussed in section 5.2.2, public sector employment can be endogenous as it may respond to overall population growth or be used as a tool to offset negative shocks to private sector employment. Therefore, I repeat the main estimates for private sector employment when the public sector contribution variable is instrumented by the weighted average of nationwide changes in public employment using two-stage least square estimation. Panel C of Table 5.2 presents the first-stage estimates for the IV model. The first-stage regression has a high explanatory power and the instrument contributes considerably to this fit. As indicated by the positive and highly significant point estimates, it accounts for significant variation in public sector employment growth, with t-ratios of around six in all specifications. In the fully augmented specification, the partial R^2 between public sector employment and the instrument is reassuringly high at .177. In none of the specifications, the F-statistic for the significance of the instrument excluded from the structural model is smaller than 33, so the weighted national growth of public sector employment seems to be an appropriate instrument for public sector contribution.

Panel B of Table 5.2 presents the second-stage results for the instrumental variable model. The 2SLS estimates are negative, precisely estimated and give a lower estimate for β compared to their OLS counterparts. This indicates that the OLS results suffer from upward-bias and capture some reverse causality in the sense that private sector employment causes the creation of public sector employment, and not vice versa. In the fully specified model (column 6), the coefficient translates into a loss of approximately 7.4 jobs in the private sector for any 10 additional public sector jobs. When comparing these results to the estimates obtained by Faggio and Overman (2014), it is noticeable that, for the same time span, the authors do not find a significant impact of public sector employment growth on the evolution

Table 5.2: Effects of Public Sector Growth on Private Sector Employment: OLS and IV

	(1)	(2)	(3)	(4)	(5)
			Panel A: OLS estimates		
Contribution public	-.522***	-.520***	-.595***	-.602***	-.574***
	(.101)	(.101)	(.093)	(.107)	(.089)
Total population (log)		-.001			-.001
		(.002)			(.002)
Share medium skilled			-.131***		-.124**
			(.036)		(.060)
Share high-skilled			-.011		.129**
			(.043)		(.064)
West				.011**	.009
				(.005)	(.007)
Urban				-.004	-.016**
				(.003)	(.004)
R^2	.076	.076	.114	.091	.150
			Panel B: IV Second Stage		
Contribution public	-.682***	-.674***	-.852***	-.926***	-.738***
	(.205)	(.204)	(.233)	(.235)	(.234)
R^2	.069	.070	.096	.070	.142
			Panel C: IV First Stage		
Instrument Variable	2.339***	2.392***	2.082***	2.099***	2.211***
	(.353)	(.358)	(.354)	(.361)	(.353)
R^2	.239	.242	.262	.265	.273
F-test on excl. instrument	43.84	44.68	34.65	33.81	39.21

Notes: N = 402. Robust SE in parentheses. The dependent variable is the contribution of private sector to total employment growth. All controls are measured as of 2003. The instrumental variable is equal to the 2003 fraction of public employment in overall employment multiplied by the national growth of public sector employment in all but the own district between 2003 and 2007. The dependent variable in Panel C is public sector contribution. * Significant at 10%, ** at 5%, *** at 1%.

of private sector employment in the UK.

The robustness of this basic results is verified to a number of permutations of the baseline specification described by equation 5.1.[4] One threat to the identification strategy applied in this analysis is that serially correlated shocks also drive the initial share of a district's public employment. To address this concern, I construct an alternative instrument that uses the public sector employment share in the year 2000 combined with national changes in public sector employment between 2003 and 2007. As a second test, the results are replicated when observations are weighted by the start-of-period district population in order to account for differences in district sizes. Further, I aggregate the 412 administrative districts in Germany to 260 labor market regions (Koller and Schwengler, 2000), which take commuter flows into

[4]The results of these robustness checks are depicted in Appendix Table 6.5.

account and therefore reflect local labor markets more appropriately (Eckey et al., 2006). Reassuringly, in all cases I find a robust crowding out effect of public sector employment on employment growth in the private sector.

As the point estimate for β is smaller than minus unity in the baseline specification in both the OLS and the IV model, net employment must rise when public sector employment grows. More specifically, for any additional 100 jobs that are created in the public sector, net employment should rise by 26 jobs. These employment increases can result from decreases in unemployment or from increases in the labor force if some previously inactive people become active. Further, it may be that new residents migrate from other districts. In order to analyze along which margin employment adjusts, I estimate variants of equation 5.1, where the dependent variables represent the change in the local labor force, the change in unemployment as well as the change in net migration between 2003 and 2007. For ease of comparison, all variables are normalized by total initial district employment. The 2SLS results are presented in Table 5.3.[5] Columns 1, 3 and 5 depict the results with public sector contribution as the only explanatory variable, while the specifications in column 2, 4 and 6 include the full set of control variables used in column 5 of Table 5.2.

Table 5.3: Effects of Public Sector Growth on Unemployment and Migration: 2SLS Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Δ Labor Force		Panel B: Δ Unemployment		Panel C: Δ Net migration	
Contr. public	.754**	.175	.435**	-.087	-.086	.047
	(.315)	(.303)	(.186)	(.173)	(.069)	(.077)
Covariates	no	yes	no	yes	no	yes
F-stat	43.84	39.21	43.84	39.28	43.48	41.11

Notes: N = 402. Robust SE in parentheses. Controls are used as indicated in Table 5.2. All controls are measured as of 2003. The dependent variables are the change in the local labor force, in the number of unemployed and in net migration between 2003 and 2007, normalized by total district employment in 2003. The instrumental variable is equal to the 2003 fraction of public employment in overall employment multiplied by the national growth of public sector employment in all but the own district between 2003 and 2007. * Significant at 10%, ** at 5%, *** at 1%.

The results in Panel A and B suggest that public employment growth leads to an increase in the local labor force and to a decrease in unemployment. The point estimates imply that out of the 26 jobs created, twice as much are filled by employees who were previously inactive than by workers who were unemployed. However, in the fully specified model, neither of the estimated coefficients is significantly different from zero. The results for net migration in Panel C show that the migration adjustments to regional public sector employment growth are positive but relatively small in size and imprecisely estimated. Yet, it is important to note that this result strengthens the validity of the local labor market approach. If mobility responses were large, local impacts on wages and employment would rapidly diffuse across regions and be hard to identify (Autor et al., 2013).

[5]The corresponding OLS results are presented in Appendix Table 6.6

5.4.2 Effect Heterogeneity by Sector

So far, I have presented robust evidence that public sector employment has substantial crowding out effects on private sector employment. The theoretical framework outlined in section 5.2.1 suggest that those negative spillovers should vary considerably across industries. That is, public employment should crowd out employment in tradable industries but have positive spillover effects on nontradable industries. In this section, this prediction is inspected in more detail. Because the employment data from the Federal Statistical Office does not provide detailed information on sectoral employment at the district level, I perform this part of the analysis using the Sample of Integrated Employment Biographies which provides industry codes down to the 5-digit SIC2003 level. Unfortunately, the SIAB lacks a measure of public and private sector employment. As discussed in detail in section 5.3, private employment is therefore constructed as in Faggio and Overman (2014). In order to assess the degree to which this affects the results, I first replicate the analysis from the previous section and estimate the effect of public sector employment on overall private employment. The IV results for this regression are presented in Panel A of Table 5.4.[6]

The 2SLS estimates in column 1 and 2 have a negative sign and are statistically significant once the regional controls are included. The size of the point estimate in column 2 is somewhat smaller than the coefficient that is obtained when performing the analysis with employment data from the Federal Statistical Office (see column 5 in Table 5.2). One explanation for the different magnitudes is that the SIAB results abstract from substitution effects of private sector activity in sectors that are traditionally dominated by public sector provision (e.g. health care and education) as these industries are excluded from the analysis. Further, the point estimate is statistically less significant, which is likely to result from measurement error.

Table 5.4: Effects of Public Sector Growth on the Tradable and Nontradable Sector: 2SLS Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Private Employment		Panel B: Tradable		Panel C: Nontradable	
Contribution public	-.165	-.528*	-.612**	-.560**	.447***	.125
	(.257)	(.303)	(.236)	(.284)	(.125)	(.125)
Covariates	no	yes	no	yes	no	yes
F-stat	43.79	38.40	43.78	41.55	43.78	41.55

Notes: N = 402. Robust SE in parentheses. Each cell corresponds to a single regression. The dependent variable is the contribution of private sector to total employment growth. Controls are used as indicated in Table 5.2. All controls are measured as of 2003. The instrumental variable is equal to the 2003 fraction of public employment in overall employment multiplied by the national growth of public sector employment in all but the own district between 2003 and 2007. * Significant at 10%, ** at 5%, *** at 1%.

The comparison of results using both datasets suggests that one can be reasonably confident in using the SIAB data to analyze heterogeneous effects across sectors, although substitution

[6]The corresponding OLS results are depcited in Appendix Table 6.7.

effects in the tradable sector might be somewhat underestimated. Bearing in mind this limitation, I estimate models described by equation 5.1 separately for the tradable and the nontradable sector, where the sector classification follows Dustmann et al. (2014). The sector-specific results are depicted in Panel B and C of Table 5.4. Consistent with expectations, the coefficients on tradable employment in column 3 and 4 are negative and statistically significant. The estimated effect of public employment growth on the nontradable sector is positive but imprecisely estimated in the fully specified model (column 6). When comparing my estimates to the results obtained in Faggio and Overman (2014), it is interesting to note that the effects are broadly similar in the tradable sector. Yet, in contrast to what has been found in the UK, I was not able to find conclusive evidence for positive multiplier effects on the nontradable sector in Germany. One possible explanation for the different results is that labor market rigidities, such as the more generous benefit system in Germany, reduce the labor supply elasticity, which in turn decreases the size of the positive local multiplier effect on nontradable industries. In addition, those positive multiplier effects result from increases in net wages, while the negative spillover effects on the tradable sector are caused by increases in gross wages. Hence, the different findings in the nontradable sector may be attributable to the fact that Germany has a more progressive tax system than the UK.

5.4.3 Effects on Wages

A central prediction of the conceptual framework in Faggio and Overman (2014) is that increased public sector employment raises local wages. While an increase in local income raises the demand for nontradable goods and employment in this sector, local wage increases deteriorate the competitiveness of tradable industries, eventually affecting employment in the private sector. To consider the impact of public sector employment on wages in the private sector, I estimate log wage regressions as described by equation 5.3.

Table 5.5: Effects on Gross Daily Wages in the Tradable and Nontradable Sector: 2SLS estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Private Employment		Panel B: Tradable		Panel B: Nontradable	
Contribution public	.029***	.022***	.033***	.024***	.016***	.016***
	(.012)	(.008)	(.013)	(.009)	(.005)	(.005)
Occupation ctrls.	no	yes	no	yes	no	yes
Industry ctrls.	no	yes	no	yes	no	yes
R^2	.620	.657	.611	.656	.643	.656

Notes: N = 1,320,066/967,168/352,898 in Panels A/B/C. All models include an intercept, dummies for education levels, potential experience and its square, dummies for part-time employment, foreign citizenship, and interactions of all individual level controls with the time dummy. Observations are weighted by the length of a worker's employment spell in a given year. The instrument is interacted with a dummy for the observations of year 2007. Robust standard errors in parentheses are clustered at the district level. * Significant at 10%, ** at 5%, *** at 1%.

Panel A of Table 5.5 presents the IV estimates of log gross daily wages for the entire private sector.[7] The first column includes worker-level characteristics as controls (age, age^2, dummies for foreign citizenship, education levels, working time arrangement), each interacted with time dummies. The second column includes dummies for seven broad occupational categories as well as 13 broad industry indicators and their interaction with a dummy for the year 2007. In both specifications, the point estimates are positive and highly significant, indicating that public sector employment creates upward pressure on wages in the private sector, which is in line with the theoretical considerations in Faggio and Overman (2014). The point estimate in column 2 suggests that an increase in public sector contribution by 1 percentage point causes wages in the private sector to rise by 2.2 percent. Panel B and C of Table 5.5 repeat these estimates separately for the tradable and the nontradable sector. The positive and significant coefficients demonstrate that wages rise in both sectors, although the increase is somewhat more pronounced in the tradable sector.

5.5 Conclusion

Making up for about 11% of overall employment, the public sector is the largest employer in Germany. By analyzing local labor markets, this study explores the consequences of public sector employment on the private sector. To do so, I relate changes in private sector employment and earnings across German local labor markets to changes in public sector employment growth. My findings suggest that public sector employment growth has substantial crowding out effects on the private sector. In particular, 100 public sector jobs crowd out 74 private jobs. In addition, this study presents evidence that public sector employment growth exerts significant upward pressure on local wages in the private sector. Consequently, employment losses are not evenly distributed across industries. Instead, the crowding out effect of public sector employment mainly accrues to the tradable sector, where wage increases deteriorate the competitiveness of the local industries. As opposed to this, employment in the nontradable sector is relatively unaffected because negative effects resulting from wage increases are offset by rising local demand for nontradable goods. The results of this study suggest that when governments attempt to increase employment levels by creating public employment programs, it is crucial to consider potential negative spillover effects on the private sector.

[7]The corresponding OLS results are depcited in Appendix Table 6.7.

6 Appendix

6.1 Appendix to Chapter 2 "The Polarization of Employment in German Local Labor Markets"

6.1.1 Data Appendix

Processing SIAB Data and Sample Description

All information concerning local employment and wages are obtained from the Sample of Integrated Labor Market Biographies Regional File (SIAB-R), a two percent random sample drawn from the full population of the Integrated Employment Biographies that provides detailed information on daily wages for employees subject to social security contributions. We express employment in full-time equivalents, following the weighting procedure as proposed by Dauth (2013) and weigh part-time employment using information on whether an individual works full-time, major part-time or minor part-time: labor supply of individuals working minor part-time (less than 18 hours) is multiplied with 16/39 and major part time (18 to less than 39 hours) is multiplied by 24/39, respectively.

In our analysis we exclude marginal employment as this information is only available from 1999 onwards and delete parallel employment spells. If available, missing values for nationality, occupation and location of an individual are imputed based on the most recent spells of the same individual. Education levels are aggregated into three groups: employees with no occupational training are considered as having a *low* level of education; employees with a vocational occupation who have completed an apprenticeship or graduated from a vocational college are classified as *medium* educated and employees holding a university or technical college degree are considered *highly* educated. Missing information on education levels is imputed following Fitzenberger et al. (2006).

In our wage analysis we restrict the sample to full-time employees as employment and wage information is reported on a daily basis and lacks information on hours worked. Therefore, wages for part-time employment are measured less accurately. All wages are converted in Euros at constant 2000 prices using the German consumer price index (CPI) for all private households. As price level data and price indices are not available at the regional level we are forced to use a common deflator for all labor market regions. We correct for the right-censoring of wage records at the social security contribution threshold by imputing and replacing the topcoded wages following Gartner (2005). We run a series of tobit regressions of log wages in each year, separately by gender and the three education groups, including age and its square, a vector of region fixed effects and a set of industry and occupation fixed effects. Topcoded wages are then replaced by draws from normal distributions that are truncated and whose moments are determined from the tobit estimation. Since 1984, one-time and bonus payments have been included in the wage measure, resulting in a spurious increase in earnings inequality (Steiner and Wagner, 1998). We account for this structural break by correcting the wage observations before 1983 following Fitzenberger (1999) and Dustmann et al. (2009). As the additional payments generally only affect relatively high wages, it is assumed that only wages above the median need to be corrected. Hence, we run a linear regression of wage growth, where wage growth up to the median is assumed to be constant. The percentage difference between the quantile from the upper half of the distribution and the median can be interpreted as "excessive" wage growth and is used to correct wages before 1983. We thank Bernd Fitzenberger and Christian Dustmann for making the correction program available to us. Results of these regressions are available upon request.

Due to data protection reasons the SIAB-R is anonymized and occupational information is aggregated to 120 occupation groups. However, occupations are unambiguously assignable to the three-digit 1988 occupational classification which we use to construct occupational task shares in the BIBB/IAB qualification and career survey.

Computing Regional Unemployment and Migration Rates using SIAB-R

Unemployment Rates For the construction of regional unemployment rates separately by gender we rely on the benefit recipient history included in the SIAB-R, which provides information on periods during which individuals receive earnings-replacement benefits (unemployment benefit, unemployment assistance and maintenance allowance) from the Federal Employment Agency (Bundesagentur für Arbeit, BA). Due to data limitations we are forced to conduct our analysis on unemployment responses for the shorter time period 1981 to 2004. On the early end we are limited because the benefit receipt data up to 1980 are only partially recorded (Dorner et al., 2011). A change in legislation in 2005 limits a consistent analysis of unemployment trends after this year.

We measure the regional unemployment rate as the sum of days residents were registered as unemployed relative to total days worked in a given year and a given region. With the data stemming from the SIAB-R, unemployment information is only available for workers who were previously employed subject to social security contributions. To validate the robustness of our results, we compare our self-computed unemployment rate with administrative records provided by the Statistics Department of the German BA that publishes a time series on district level data on the overall unemployment rate starting in 1985. Unfortunately, further splits by age groups, gender and citizenship are only available at the district level from 1998 onwards. Our self-computed measure and the official unemployment rate are highly correlated in the years after 1985, with the correlation coefficient varying between .81 and .92. In addition, we regress the change in the unemployment rate for the pooled sample between 1985 and 2004 (were we have reliable data from both sources) on the routine share in 1979 using both definitions of the unemployment rate and obtain similar coefficients from both specifications. All results are available from the authors upon request.

Migration Rates Unfortunately, official data on the number of inward- and outward-migrants on the regional level separately for males and females is not fully available from 1979 on. Therefore, we construct migration shares for the years 1979 and 2006 using information on the workplace location available in the SIAB-R. Total regional inmigration is defined as the sum of workers, who have changed job from some region into a certain region. Analogously, total outmigration is defined as the sum of workers in one region, who have changed their jobs towards a workplace that is located in a different region.

6.1.2 Table Appendix

Table 6.1: Estimated Impact by Age, Education and Working Time, 1979 - 2006

	Outcome measures among:					
	Age<40	Age≥40	Low-skilled	Medium-skilled	Part-time	Full-time
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Services					
Routine Share 1979	.097	.160**	.143	.037	.313	.114**
	(.070)	(.079)	(.132)	(.060)	(.201)	(.056)
R^2	.170	.109	.139	.129	.167	.177
	Panel B: Construction					
Routine Share 1979	.126**	.307***	.227***	.191***	.002	.186***
	(.062)	(.085)	(.086)	(.062)	(.030)	(.058)
R^2	.257	.293	.217	.291	.078	.259
	Panel C: Professional, Managerial, Technical					
Routine Share 1979	.026	-.006	-.021	.012	.088	.015
	(.054)	(.067)	(.047)	(.062)	(.148)	(.051)
R^2	.150	.108	.220	.164	.108	.145
	Panel D: Clerical, Sales					
Routine Share 1979	-.074	-.077	.075	-.137*	-.044	-.063
	(.083)	(.093)	(.108)	(.076)	(.185)	(.075)
R^2	.147	.263	.194	.222	.296	.198
	Panel E: Production, Operators					
Routine Share 1979	-.175	-.385***	-.423**	-.103	-.360*	-.251**
	(.112)	(.107)	(.199)	(.106)	(.218)	(.101)
R^2	.189	.222	.200	.215	.461	.229

Notes: $N = 204$ labor market regions. All models include a constant, dummies for the federal state in which the region is located, a measure of population density (number of inhabitants per square kilometer) as well as the covariates listed in Table 2.4. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

6.1.3 Figure Appendix

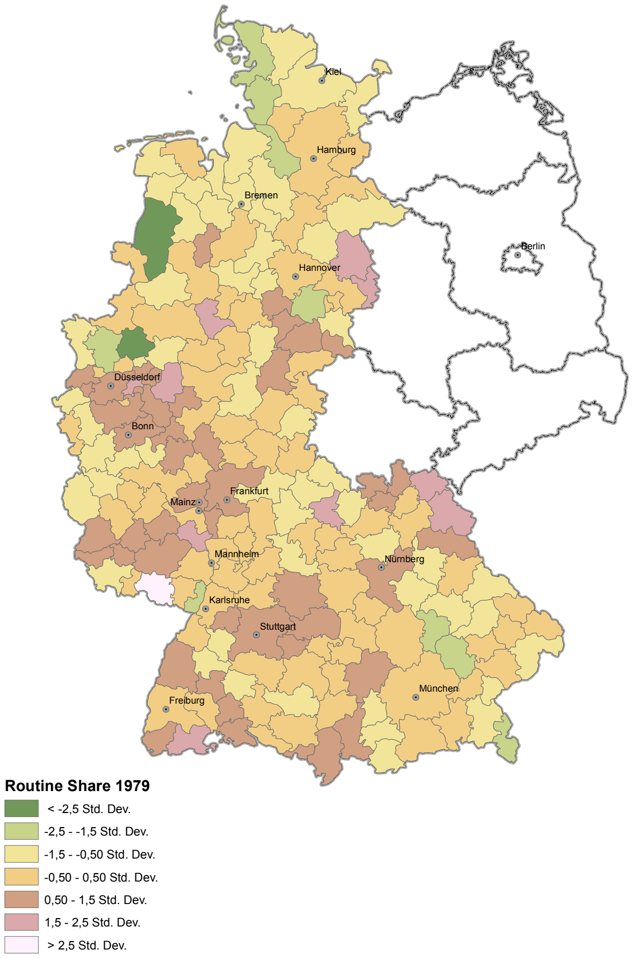


Figure 6.1: Distribution of Routine Share 1979

6.2 Appendix to Chapter 3 "Spatial Wage Inequality and Technological Change"

6.2.1 Data Appendix

Processing SIAB Data and Sample Description

All information concerning local employment and wages were obtained from the Sample of Integrated Labor Market Biographies Regional File (SIAB-R), a two percent random sample drawn from the full population of the Integrated Employment Biographies. We exclude public sector and agricultural workers from our sample and focus on full-time employment only, as employment and wage information is reported on a daily basis and lacks information on hours worked. Furthermore, we exclude marginal employment as this information is only available from 1999 onwards and delete parallel employment spells. If available, missing values for the nationality of an individual are imputed based on the most recent spells of the same individual. Education levels are aggregated into three groups: employees with no occupational training are considered as having a *low* level of education; employees with a vocational occupation who have completed an apprenticeship or graduated from a vocational college are classified as *medium* educated and employees holding a university or technical college degree are considered *highly* educated. Missing information on education levels is imputed following Fitzenberger et al. (2006).

All wages are converted to Euros at constant year 2000 prices using the German consumer price index (CPI) for all private households. As price level data and price indices are not available at the regional level we are forced to use a common deflator for all labor market regions. We correct for the right-censoring of wage records at the social security contribution threshold by imputing and replacing the topcoded wages following Gartner (2005). We run a series of tobit regressions of log wages in each year, separately by gender and the three education groups, including age and its square, a vector of region fixed effects, and a set of industry and occupation fixed effects. Topcoded wages are then replaced by draws from normal distributions that are truncated and whose moments are determined from the tobit estimation. Since 1984, one-time and bonus payments have been included in the wage measure, resulting in a spurious increase in earnings inequality (Steiner and Wagner, 1998). We account for this structural break by correcting the wage observations before 1983 following Fitzenberger (1999) and Dustmann et al. (2009). As the additional payments generally only affect relatively high wages, it is assumed that only wages above the median need to be corrected. Hence, we run a linear regression of wage growth, where wage growth up to the median is assumed to be constant. The percentage difference between the quantile from the upper half of the distribution and the median can be interpreted as "excessive" wage growth and is used to correct wages before 1983. We thank Bernd Fitzenberger and Christian Dustmann for making the correction program available to us. The results of these regressions are available upon request.

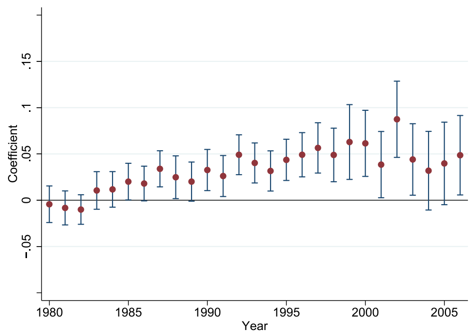
6.2.2 Table Appendix

Table 6.2: Technology and Task Inputs, 1979 - 2006

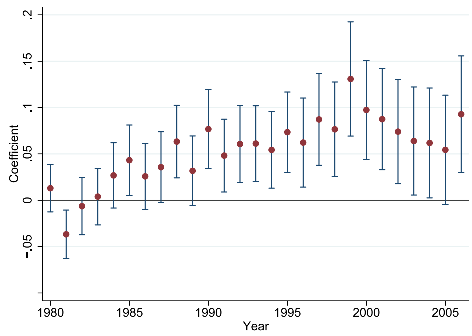
	Outcome Measures Among:						
	All	Males	Females	Age<40	Age>40	Less-skilled	High-skilled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Results for Task Supplies							
ΔT^R							
RSH_{1979}	-.401***	-.382***	-.439***	-.404***	-.395***	-.397***	-.474***
	(.035)	(.040)	(.050)	(.044)	(.038)	(.036)	(.111)
R^2	.848	.765	.696	.797	.811	.854	.444
ΔT^C							
RSH_{1979}	.128***	.126***	.115**	.125***	.126***	.116***	.448***
	(.036)	(.038)	(.045)	(.048)	(.035)	(.037)	(.109)
R^2	.778	.707	.733	.712	.720	.796	.342
ΔT^M							
RSH_{1979}	.273***	.256***	.324***	.279***	.269***	.281***	.026
	(.026)	(.029)	(.043)	(.032)	(.035)	(.026)	(.045)
R^2	.638	.555	.402	.577	.496	.623	.122
Panel B: Results for Task Compensation							
$\Delta ln(w^R)$							
RSH_{1979}	-.362	-.265	-.360	-.312	-.495*	-.389	-.516
	(.272)	(.292)	(.407)	(.313)	(.277)	(.243)	(1.636)
R^2	.269	.386	.248	.311	.296	.330	.120
$\Delta ln(w^C)$							
RSH_{1979}	.404**	.202	1.079***	.383	.495**	.444**	.426
	(.174)	(.177)	(.284)	(.236)	(.208)	(.199)	(.407)
R^2	.547	.367	.412	.438	.476	.439	.155
$\Delta ln(w^M)$							
RSH_{1979}	-.701	-.230	-2.895***	-.990	-.750	-1.850**	3.740
	(.460)	(.764)	(.910)	(.955)	(.736)	(.884)	(4.028)
R^2	.396	.393	.334	.283	.229	.471	.297

Notes: $N = 204$ labor market regions. All models include dummies for the federal state in which the region is located and covariates reflecting the human capital and demographic composition outlined in column (6), Table 6.2 as well as a constant. Models are weighted by start of period share of national population. Robust standard errors in parentheses. * Significant at 10%, ** at 5%, *** at 1%.

6.2.3 Figure Appendix



(a) Estimated Impact of Technological Change on the Theil-Index



(b) Estimated Impact of Technological Change on the P85/P15-Ratio

Figure 6.2: Dynamic Wage Patterns of the Routinization Effect

Notes: Each panel plots the regression coefficients and 90% confidence intervals obtained from up to 26 regressions. The regressions relate each outcome measured during the year indicated, to the regional technology exposure. All regressions include covariates reflecting the human capital and demographic composition outlined in column (6), Table 6.2.

6.3 Appendix to Chapter 4 "Product Market Deregulation and Employment Outcomes: Evidence from the German Retail Sector"

6.3.1 Data Appendix

Sales Data

The data on sales are collected from the Regional Statsistical Offices. The dataset consists of monthly observations of sales at the spatial unit of federal states, normalized to a reference level. Information is available on nominal as well as real sales, which are deflated by the the consumer price index (CPI) based on all consumer goods. In each federal state, a panel of establishments is randomly sampled from the industry register, which covers establishments whose annual sales exceed 250,000 Euro. Because sampled establishments are obliged by law to take part in the survey, the data set does not suffer from self-selection.

The sample period is restricted to January 2006 to December 2008 for the following reasons: On the early end I am limited because as of 2006, refreshment samples were included in a number of states, leading to a structural break in the time series. After 2008, the industry classification change, and a one-to-one mapping between the two classifications is not possible due to the high level of aggregation. Information on sales volumes in Lower Saxony is only available from July 2007 onwards. Hence, the final dataset consists of 576 state-month-observations.

Data on Prices

The data on prices is obtained from the Regional Statistical Offices, which publish state level CPIs on a monthly basis. Two federal states, namely Hamburg and Schleswig-Holstein, do not publish state level price indices and hence have to be excluded from the analysis. The CPI is calculated according to Laspeyre's formula, with the reference year for the entire time series being 2010. Overall, the dataset consist of 1008 state-month observations.

Apart from an overall price index, which is based on all consumer goods, price information is also consistently available for 12 main groups. From these, I restrict the analysis to the following: food and nonalcoholic beverages (group 1), apparel and shoes (group 3), and furniture (group 5).

6.3.2 Table Appendix

Table 6.3: Robustness Checks: Excluding Individual States

	(1)	(2)	(3)
Schleswig-Holstein	-.018**	-.017***	-.015***
	(.008)	(.004)	(.005)
Hamburg	-.018**	-.017***	-.015***
	(.008)	(.003)	(.005)
Lower Saxony	-.015**	-.018***	-.015***
	(.007)	(.004)	(.005)
Bremen	-.018**	-.017***	-.015***
	(.008)	(.003)	(.005)
North Rhine-Westphalia	-.021**	-.018***	-.016***
	(.008)	(.004)	(.005)
Hesse	-.019**	-.017***	-.015***
	(.008)	(.003)	(.005)
Rhineland-Palatinate	-.017**	-.018***	-.016***
	(.009)	(.004)	(.006)
Baden-Wurttemberg	-.022**	-.016***	-.015***
	(.008)	(.004)	(.005)
Berlin	-.019**	-.017***	-.015***
	(.008)	(.003)	(.005)
Brandenburg	-.018**	-.016***	-.014**
	(.008)	(.003)	(.005)
Mecklenburg-West Pomerania	-.018**	-.017***	-.017***
	(.008)	(.003)	(.003)
Saxony	-.018**	-.017***	-.015***
	(.008)	(.003)	(.005)
Saxony-Anhalt	-.019**	-.017***	-.015***
	(.008)	(.003)	(.005)
Thurangia	-.019**	-.017***	-.015**
	(.008)	(.004)	(.005)
Add. Controls	yes	yes	yes
District × time trends	no	yes	yes
District × time^2 trends	no	no	yes

Notes: N=3,248. Each cell reports the coefficient on the treatment variable for one regression. Each row indicates, which federal state is excluded from the regression. All regressions include district and year fixed effects. Standard errors in parentheses are clustered at the federal state level. * Significant at 10%, ** at 5%, *** at 1%.

Table 6.4: Robustness Checks: Excluding Individual Years

	(1)	(2)	(3)
2003	-.021**	-.012***	-.014***
	(.008)	(.003)	(.005)
2004	-.021**	-.017***	-.015**
	(.008)	(.003)	(.006)
2005	-.017**	-.014***	-.013***
	(.008)	(.003)	(.004)
2006	-.0163*	-.011**	-.014**
	(.008)	(.004)	(.007)
2007	-.025**	-.047***	-.044***
	(.010)	(.009)	(.008)
2008	-.016*	-.013***	-.007**
	(.008)	(.004)	(.003)
2009	-.016**	-.016***	-.015***
	(.007)	(.003)	(.005)
2010	-.017**	-.017***	-.007**
	(.006)	(.004)	(.003)
Add. Controls	yes	yes	yes
District $\times$ time trends	no	yes	yes
District $\times$ time^2 trends	no	no	yes

Notes: N=3,248. Each cell reports the coefficient on the treatment variable for one regression. Each row indicates, which year is excluded from the regression. All regressions include district and year fixed effects. Standard errors in parentheses are clustered at the federal state level. * Significant at 10%, ** at 5%, *** at 1%.

6.3.3 Figure Appendix

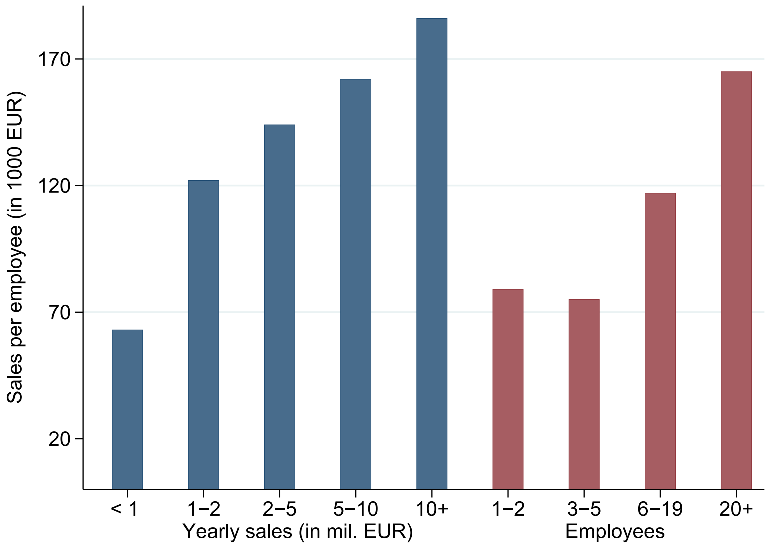


Figure 6.3: Sales per Employee in 2005, Differentiated by Establishment Size

Notes: Data source: Federal Statistical Office.

6.4 Appendix to Chapter 5 "Public Sector Employment and Local Multipliers"

6.4.1 Table Appendix

Table 6.5: Effects on Private Sector Employment: Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel C: Instrument		Panel A: Weighted		Panel B: LMR	
Contribution public	-1.374***	-1.283**	-.713***	-.843***	-.842***	-1.037***
	(.475)	(.417)	(.211)	(.248)	(.146)	(.166)
Covariates	no	yes	no	yes	no	yes
R^2	.019	.159	.084	.118	.293	.347
F-stat	22.106	20.462	45.377	37.262	26.592	17.402
Observations	402	402	402	402	260	260

Notes: Robust SE in parentheses. Controls are used as indicated in Table 5.2. All controls are measured as of 2003. The instrumental variable is equal to the 2003 fraction of public employment in overall employment multiplied by the national growth of public sector employment in all but the own district between 2003 and 2007. * Significant at 10%, ** at 5%, *** at 1%.

Table 6.6: Effects of Public Sector Growth on Unemployment and Migration: OLS Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Δ Labor Force		Panel B: Δ Unemployment		Panel A: Δ Net migration	
Contribution public	0.877***	0.535***	0.399***	0.110	-0.052	-0.022
	(.195)	(.145)	(.135)	(.105)	(.033)	(.034)
Covariates	no	yes	no	yes	no	yes
R^2	.112	.415	.074	.628	.010	0.112

Notes: N = 402. Robust SE in parentheses. The dependent variables are the change in the local labor force, in the number of unemployed and in net migration between 2003 and 2007, normalized by total district employment in 2003. Controls are used as indicated in Table 5.2. All controls are measured as of 2003. * Significant at 10%, ** at 5%, *** at 1%.

Table 6.7: Effects of Public Sector Growth on the Tradable and Nontradable Sector: OLS Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Private Sector		Panel B: Tradable		Panel B: Nontradable	
	Dependent Variable: Employment					
Contribution public	.072	.010	-.146	-.041	.214	.045
	(.121)	(.123)	(.108)	(.107)	(.056)	(.056)
Covariates	no	yes	no	yes	no	yes
R^2	.001	.052	.005	.064	.028	0.188
	Dependent Variable: Wages					
Contribution public	.018***	.015***	.019***	.015***	.013***	.013***
	(.005)	(.005)	(.006)	(.005)	(.003)	(.003)
Covariates	no	yes	no	yes	no	yes
R^2	.620	.658	.612	.655	.643	.656

Notes: N = 402. Robust SE in parentheses. Each cell corresponds to a single regression. The dependent variable is the contribution of private sector to total employment growth. Controls are used as indicated in Table 5.2. All controls are measured as of 2003. * Significant at 10%, ** at 5%, *** at 1%.

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Selbstständigkeitserklärung

Ich erkläre, dass ich die vorliegende Arbeit selbstständig und nur unter Verwendung der angegebenen Literatur und Hilfsmittel angefertigt habe.

Ich bezeuge durch meine Unterschrift, dass meine Angaben über die bei der Abfassung meiner Dissertation benutzten Hilfsmittel, über die mir zuteil gewordene Hilfe sowie über frühere Begutachtungen meiner Dissertation in jeder Hinsicht der Wahrheit entsprechen.

Berlin, den 09.01.2015 Charlotte Cornelia Senftleben-König, geb. Senftleben,